

**Gordon Institute
of Business Science**
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**Capital asset pricing model (CAPM) applicability in the South African context and
alternative pricing models**

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Abstract

The ability to accurately price equity is an ineluctable requirement within businesses where decisions need to be taken daily that impact upon the future viability of that business.

The Capital asset pricing model (CAPM) is the preeminent tool that has become entrenched within academia and business for exactly the purpose of costing equity capital.

This study aimed to prove whether the application of the CAPM, in various forms, including the Black's CAPM, was merely a myopic inculcation of the academic and business spheres, or whether it truly reflected the empirical reality of the South African markets.

The research discredited eight variations of the CAPM through a quantitative causal design, which employed t-tests and ANOVAs, tested upon a judgmental sample of the largest 160 shares on the JSE. Reaching this opprobrium would have been a Pyrrhic victory, had an alternative model not been proposed.

Thus, a quartet of styles was employed in tests against both non-resource and resource shares in an attempt to generate two multi-factor models known as the Optimised Returns Score (ORS) combined models. The generated model for the non-resource shares explained 36.5% of the variation in the observed cost of equity capital, at a 95% level of significance. However, a statistically significant predictive model for resource shares was unable to be found, possibly due to the small sample size available.

Keywords

CAPM, Alternative, Equity Cost, JSE, ORS combined model

Declaration

I declare that this research project is my own work. It is submitted in partial fulfilment of the requirements for the degree of Master of Business Administration at the Gordon Institute of Business Science, University of Pretoria. It has not been submitted before for any degree or examination in any other University. I further declare that I have obtained the necessary authorisation and consent to carry out this research.

Brad Carter

Date

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Chapter 1 Introduction to Research Problem

1.1 Research Title

Capital asset pricing model (CAPM) applicability in the South African context and alternative pricing models.

1.2 The Research Problem

The capital asset pricing model (CAPM) has been the preeminent method for estimating the expected return that invested equity capital should attract since first being classified in the 1960s (Lintner, 1965; Markowitz, 1952; Mossin, 1966; Sharpe, 1964). Damodaran (2012) and Kumar and Gregory (2013), found that it was still used in most industries as the basis for investment decision making. Additionally, Correia and Cramer (2008) found that it was also widely used within the South African context. Furthermore, mainstream business media, such as the South African Business Day, also regarded it as a generally accurate method of forecasting expected returns (Harford, 2014).

The apparent logical simplicity of the CAPM and its use of only three easily estimable variables to determine the cost of the equity capital, also referred to as the returns on that equity, is inherently appealing (Ward & Muller, 2015b). The three variables namely the risk free return achievable, the specific firm's risk profile in relation to the market, and the market's average return over and above that of the risk free rate all appear to be logically related to the cost of the equity making the CAPM that much more appealing.

However, there has been recent research that has empirically questioned the validity of the CAPM, and found it to be lacking, including in the South African financial markets (Ward & Muller, 2012). Contrary to these findings, Strydom and Charteris (2013) found that the CAPM, with some alterations, did model the empirical results. Thus, a need existed for the CAPM as a tool to be carefully examined. Furthermore, if required, any improvements, or improved alternatives, could potentially have improved the investment decision making in numerous industries and redefined the academic theory.

1.2.1 Importance to Academia

Ward & Muller (2015b, p. 2) noted that the CAPM had a certain “parsimonious elegance” which made it appealing to, amongst others, academics. This inherent simplicity was what made the CAPM the most widely taught pricing model in the majority of financial courses (Damodaran, 2012; Ward & Muller, 2015b).

The abundance of research that was cited throughout this paper bore testimony to the continued and sustained interest in the CAPM, and how it had remained prevalent in the academic discourse.

The CAPM itself was borne out of the work of numerous academics rather than being the work of a single researcher, with Lintner (1965), Markowitz (1952), Mossin (1966) and Sharpe (1964) being jointly credited with its development. Their research was held in such high regard that the CAPM became widely utilised without being earnestly questioned until 1992 (Ward & Muller, 2012).

However, whilst there was limited questioning of its applicability, there were research efforts to improve the CAPM with Black (1972) showing that the CAPM formula could be improved through an alternative risk free rate, based on a minimum variance efficient zero-beta portfolio. Chou and Lin (2002), Fama and MacBeth (1973), Morgan (1975) and Stambaugh (1982) found that this variation of the model delivered an improved fit to actual financial results.

However, in the iconoclastic work of Fama and French (1992) they empirically disproved the applicability of the CAPM to the American financial markets. Furthermore, Fama and French continued to research alternative models for pricing equity capital through to 2015 due to their underlying belief that equity could be better costed (Fama & French, 1993, 2004, 2012, 2015).

Apart from Fama and French, numerous other authors from Pettengill, Sundaram and Mathur (1995) right through to more recent work by Frazzini and Pedersen (2014) concurred that the CAPM proved to be a poor fit to empirical data in the international financial markets.

Spurred on by the failures of the CAPM in these pieces of empirical research, numerous researchers turned to alternative methods for pricing the equity

capital that could be utilised to replace the CAPM. The authors ranged from Haugen and Baker (1996) through to the meta-study by Harvey, Liu and Zhu (2014) which found that, using highly regarded working papers and publications in internationally recognised academic journals, 316 different characteristics had been proposed that purported to be improved indicators of equity returns.

This academic interest was not only external to the South African market, as evidenced by the earliest research from Bradfield, Barr and Affleck-Graves (1988) through to the more recent research of Ward and Muller (2012), Strydom and Charteris (2013) and most recently that of Ward and Muller (2015b) who tested the applicability of the CAPM in the South African market.

South African researchers also had numerous publications that identified alternative methods for the pricing of equity capital. From Van Rensburg and Robertson (2003) through to Muller and Ward (2013), all showing that certain characteristics, not found in the CAPM, had significant correlation with the equity returns.

As evidenced here, the CAPM had garnered sustained interest from international and South African academics, despite the contrasting outcomes in their research. Furthermore, the research into viable alternatives had continued, both internationally and in South Africa, clearly demonstrating the ongoing importance afforded to equity pricing by academia.

1.2.2 Importance to Business

The ability to make investments that could consistently outperform the market was described as the “holy grail” (Muller & Ward, 2013, p. 1). Hence, the CAPM, which was a key constituent of the traditional discounted cash flow valuation method, was a fundamental portion of this “holy grail”.

Graham and Harvey (2001), found that, particularly amongst larger firms with more advanced valuation techniques, discounted valuation models and the CAPM were the preferred tools for performing valuations of both other companies and potential projects. In their research they found that the importance of net present value, that used the CAPM in its calculations, had actually increased over the last two decades prior to their research being conducted. Graham and Harvey (2001) actually surmised that the reason that

the CAPM had found a prominent place within business, may have been as a direct result of its importance to academia, and its subsequent widespread teaching in business schools, combined with its long-term usage in corporate finance practices.

Whilst Graham and Harvey (2001) conducted their research on American firms, Correia and Cramer (2008) and Du Toit and Pienaar (2005) found that the South African business environment looked very similar in terms of their reliance on the CAPM, and models based upon the CAPM. Correia and Cramer (2008), found that whilst South African Chief Financial Officers (CFOs) used multiple models simultaneously for valuing projects, their two preferred methods were dependent on discounted cash flow valuation, underpinned by the CAPM. They found that 82.1% of South African CFOs used Net Present Value (NPV) and that 78.6% of South African CFOs used Internal Rate of Return (IRR).

Even in mainstream business media, such as the South African Business Day, the CAPM was identified as being the primary tool for capital pricing (Harford, 2014).

The underlying premise of the CAPM is that greater risk leads to greater reward as seen by the positive relationship between the risk of an asset (β_i) and the expected returns on that asset ($E(\tilde{R}_i)$) in the CAPM formula, seen in Equation 1. The application of this premise was evident in many firms even in the absence of the specific identification of the CAPM.

Major financial institutions such as Citigroup (2015) and Moore Stephens (2015) specifically identified increased risk levels as being directly linked to increased potential returns. Moore Stephens (2015, para. 1) went so far as to describe the positive relationship between risk and expected return as a “rule of thumb in investing.”

Kansas (2010), also found that greater risk was correlated to greater returns in the South African markets, and cited Anglo American as being a company that epitomised this risk reward relationship in South Africa. He also surmised that this self-same risk reward relationship was the underlying driver behind the inclusion of emerging market exposure in investment portfolios, with American individual investors placing \$689 billion dollars into emerging overseas funds.

Underlying Kansas' claim was the fact that he regarded emerging markets as having higher risks (β s) when compared to the global market, rather than an individual region's market.

This pervasive usage of the CAPM and the widespread prevalence of its underlying tenet of greater risk being correlated with greater reward, indicated the high level of importance accorded to it by the mainstream business fraternity, over and above the keen interest exhibited by the academia. Hence, any improvements, or improved alternatives, bore a great potential impact upon the business fraternity in conjunction to the potential impact upon academia.

1.3 Research Purpose

Due to the clear importance of being able to cost the returns to equity capital to both the academic and business fraternities the research needed to firstly establish which models were applicable to the South African context. The existing research into the applicability of the CAPM to the South African market was conflicting. Furthermore, this lack of clarity was exacerbated due to a substantial portion of the research simply identifying broad trends rather than rigorously statistically testing the significance of these trends, and coming to irrefutable findings.

Moreover, if required, it would have been necessary to derive a model that would allow a firm to populate the necessary information and immediately calculate a projected cost of equity capital that was empirically supported.

Thus, the purpose of the research was two-fold. Firstly, the accuracy of the CAPM, as a tool for predicting expected returns on invested equity capital, needed to be tested within the South African context as Ward and Muller (2012) found that the CAPM did not apply to the reality of the South African financial markets, whilst Strydom and Charteris (2013) found that it did, in fact, reflect the returns to be expected in the South African environment. This apparent contradiction could have been as a result of either methodological differences or as a result the specific interpretations of the components of the CAPM, and subsequent calculations, or as a combination of both of these.

Some of these interpretations included the various methods available to calculate beta values and risk-free proxies, such as that used in Black's CAPM (Black, 1972).

Subsequently, an appropriate methodology was derived to test the several variations of the CAPM for validity in the South African context, in fulfilment of the initial portion of the research.

Secondly, as the CAPM, and its numerous variations, failed to adequately apply to the South African market conditions, it became prudent to examine and test alternative variables that could have impacted upon the expected equity returns. In previous research, several researchers, such as Ang, Hodrick, Xing and Zhang (2006), Fama and French (1992, 2004, 2012, 2015), Strugnell, Gilbert and Kruger (2011), Van Rensburg and Robertson (2003), Ward and Muller (2012), and Yu (2012) had proposed alternative variables, referred to as styles, that may have acted as predictors of equity returns.

Thereafter, these were aggregated into a quintile score to contain single share volatility, and tested against actual market returns to identify the correlations and build a predictive multifactor model, based on firm performance history.

This model would allow accurate determination of the cost of equity capital for a firm in the South African context. Given the existing importance afforded to calculating the cost of equity, through the use of the CAPM, by both business and academia, a more accurate model could dramatically improve the financial decision making of current financial practitioners and future generations who have yet to progress through the academic assemblies.

Chapter 2 Literature Review

2.1 Capital Asset Pricing Model (CAPM)

The Capital Asset Pricing Model in its original and most basic form is depicted in Equation 1 (Sharpe, 1964). An understanding of the constituent components was essential to understand both its appeal and relative importance, and thereafter, also the concerns surrounding it, within the academic sphere.

Equation 1: Original The CAPM

$$E(\tilde{R}_i) = R_f + \beta_i[E(\tilde{R}_m) - R_f]$$

In Equation 1,

$E(\tilde{R}_i)$ is the expected return on an asset i ;

R_f is the return on a risk-free asset, typically a treasury bill or bond rate;

β_i is the risk associated with asset i i.e. its market sensitivity;

$E(\tilde{R}_m)$ is the return on the portfolio that consists of all of the assets within the market (Black, 1972).

2.2 Proponents of the CAPM

The CAPM's formulation was collectively accredited to Lintner (1965), Markowitz (1952), Mossin (1966) and Sharpe (1964) and remained largely unquestioned until 1992 (Ward & Muller, 2012). Their contribution to financial economics, via the CAPM, was so significant that in 1990 Markowitz, Sharpe and Miller, who later helped refine the CAPM, were awarded the Nobel Prize (Ward & Muller, 2012).

Empirically, Nikolaos (2009) found that, although the CAPM did not prove to be a perfect fit for financial data from the United Kingdom, both the beta (β) and the projected risk free rate were empirically supported. Only the difference between the total market returns and the risk free rate, known as the market

risk premium, was not correctly predicted by the CAPM. Similarly, Fraser, Hamelink, Hoesli and Macgregor (2004) found that the β held a positive relationship to returns. It should, however, be noted that they were also not able to conclusively find that the CAPM, as a whole, applied to the United Kingdom's financial data. An interesting finding that they did note was that the CAPM was a better fit to the market during periods when the market was moving downwards.

On the opposite side of the Atlantic Ocean, in an analysis of the New York Stock Exchange (NYSE) data, Fama and MacBeth (1973) found similarly that there was a perfectly linear relationship between risk and return, as would be expected in an efficient market where the CAPM applied.

In focussing on emerging markets, Hearn and Piesse (2009) revealed through their research that risk free rates tended to be higher in these emerging markets. This was corroborated by Kansas (2010) when he found that the higher general risk levels, represented by β , correlated to higher returns in emerging markets.

In an early piece of research into the South African market, Bradfield et al. (1988) revealed the use of the CAPM to be empirically supported, and that the South African Government treasury bill (t-bill) rate was an accurate estimate of the risk free rate in the CAPM. Marginally more recently, van Rhijn (1995) verified Bradfield et al.'s (1988) findings.

Correia and Cramer (2008), Damodaran (2012) and Kumar and Gregory (2013) noted that the CAPM was still in widespread use throughout academia and business. Harford (2014) supported this widespread usage by asserting that the CAPM was generally an accurate model for use within the South African market.

Strydom and Charteris (2013), conducted empirical testing of the CAPM in the South African environment, using data from 1993 until 2008, utilising all of the shares on the JSE during this time period. Their results indicated that the CAPM, after being modified to remove the reliance on a risk free proxy, did indeed predict the returns that could be witnessed in the South African financial market, supporting the use of the CAPM to predict returns on equity.

2.3 Variations on the CAPM

The Capital Asset Pricing Model in its original and most basic form is depicted in Equation 1 (Sharpe, 1964). However, any variations to the formula may have impacted on the applicability of the specific variation of the CAPM. As seen in the research of Strydom and Charteris (2013), a variation in the CAPM formula utilised can bring about distinctly different conclusions from the research. The specific variation of the CAPM, which became popular, and was used by Strydom and Charteris (2013) was the Black's CAPM as expounded upon below.

2.3.1 Black's CAPM

For numerous years academics had sought to improve on the specific variables that constituted the CAPM equation. Black (1972) altered the CAPM equation to replace the so-called risk free rate (R_f) with a zero-beta portfolio to derive Equation 2, where $E(\tilde{R}_z)$ is the expected return on a zero-beta portfolio i.e. a riskless portfolio.

Equation 2: The Black's CAPM

$$E(\tilde{R}_i) = E(\tilde{R}_z) + \beta_i[E(\tilde{R}_m) - E(\tilde{R}_z)]$$

Ward and Muller (2015b) explicated upon the fact that the traditional proxies for the risk free rate of treasury bills (t-bills) and treasury bonds (t-bonds), may have been low risk financial assets, but were certainly not completely free of market risk. Daily fluctuations in yields introduced volatility and the possibility of a government default nullified the claim of being risk free (Ward & Muller, 2015b).

Thus, Black's attempt to generate an alternative truly risk free asset was entirely logical. Through the construction of a zero-beta efficient minimum variance portfolio nearly all of the market risk was removed (Black, 1972). Coincidentally, Black (1972) and Fama and MacBeth (1973) found that the zero-beta portfolio produced a significantly higher risk free rate than the risk free proxies had suggested be used in the calculation of the CAPM.

The Black's CAPM was widely utilised in research on the American financial markets by Fama and MacBeth (1973) and Morgan (1975). However, it only recently became more prevalent in South African research as Strydom and Charteris (2013) and Ward and Muller (2015b) had used the Black's CAPM to empirically test the applicability to the South African market.

2.3.2 Time Period Effect on Betas

Jagannathan and Wang (1996) extolled the perils of not adjusting for the time variations in the beta of a certain stock, and making the assumption of constant betas. As they pointed out, market shocks would affect certain industries more than others, and hence shares in the most affected industries would have experienced increases in their betas as their performance would have been more affected than that of the market as a whole. They also pointed out that a company in financial distress would be plunged even further into distress during a recession making them more reliant on leverage for their financing needs and in all probability would have driven their betas upwards (Jagannathan & Wang, 1996).

Ferson and Korajczyk (1995), empirically proved that models that assumed a constant beta performed poorly in comparison to models that adjusted the time-period over which they measured their betas.

Ward and Muller (2012), applied this rationale in their testing of the CAPM against the JSE, by utilising both a beta based upon the previous 24 months of share performance, as well as a beta based upon the previous 60 months of share performance to ensure that any short-term, or cyclical, changes in the beta were adjusted for.

2.3.3 Trade Liquidity Effect on Betas

Both Dimson (1979) and Scholes and Williams (1977) identified that infrequent trading could cause erroneous betas to be calculated, and as such they made proposals for alternative methods of calculating betas that accounted for infrequent trading.

To this end Dimson (1979) recommended utilising not only the leading estimate of beta, but a combination of one leading beta and numerous lagged beta estimates. This is shown in Equation 3

Equation 3: Dimson's Aggregated Coefficients Model

$$r_{i,t} = \hat{\alpha}_i + \sum_{k=-n}^1 \hat{\beta}_{i,k} \cdot r_{m,t+k} + \epsilon_{i,t}$$

In Equation 3,

$r_{i,t}$ is the return on share i at time t ;

$r_{m,t+k}$ is the market return at time $t + k$;

$\hat{\beta}_{i,k}$ is the estimated beta for share i at a lag of k periods in the multiple regression;

$k = -n$ is the selected number of lag periods to include in the equation.

$\epsilon_{i,t}$ captures the error

Ward and Muller (2012) elected to use 4 lag periods for their analysis of the JSE to empirically test the applicability of the CAPM in the South African market. They did, however, also note that by using the JSE All Share Index (ALSI) for their sample data, the probability of having thinly traded illiquid shares was negligible.

2.4 Opponents of the CAPM

Fama and French (1992) were the first researchers to empirically disprove the CAPM's applicability using American financial data. Twenty years later Damodaran (2012), corroborated their findings with updated data showing that the CAPM was still not applicable to the US market. Faff (2001) found similar results when testing the CAPM against Australian data.

In a continuation of their research, Fama and French (2004), found that the Security Market Line (SML) as plotted based on the empirical evidence had a significantly different slope from what would have been predicted by the CAPM. Upon closer inspection it became clear that low beta shares were grossly underestimated, and that high beta shares returns were grossly

overestimated. This led them to their eventual conclusion that there was no relationship between beta and returns, hence, disproving the underlying precept of the CAPM.

Montier (2007) had similar findings disproving the CAPM, and went on to show how certain variables captured in firms' fundamentals had far greater correlations with returns than beta.

Certain researchers not only found evidence to disprove the CAPM, but in fact found an inverse relationship between betas and returns from that predicted by the CAPM. Pettengill et al. (1995) found that high beta shares experienced below market average returns, which was supported by Frazzini and Pedersen (2014) who found that risk adjusted returns dropped as betas rose.

Baker, Bradley, and Wurgler (2011) found that from 1968 until 2008, low volatility and low beta portfolios showed long-term above average returns with very few drawdowns. The complete juxtaposition of what the CAPM would have predicted.

This unexpected phenomenon was not only observed using developed markets' data, but also emerging markets', as discovered by Lazar and Yaseer (2010) when they analysed Indian financial data.

In South Africa, another emerging market, Van Rensburg and Robertson (2003) and Strugnell et al. (2011) found there to be no risk premium paid for local shares, and hence the CAPM not being applicable.

Ward and Muller (2012, 2015b) more recently also found the CAPM not to be applicable in South Africa and as with the research of Baker et al. (2011), Frazzini and Pedersen (2014) and Pettengill et al. (1995), they found an inverse relationship between risk, as represented by beta, and returns in the South African market.

2.5 Alternative Theories for Pricing Models

With such a large contingent of researchers, as seen in section 2.4, opposing the use of the CAPM in pricing real world equity capital it became prudent for

researchers to turn their attentions to investigating alternative ways to price this capital.

Harvey et al. (2014) conducted a meta-study of all of the characteristics, known as styles, which had been mooted as potential predictors of returns, or viewed differently, as the potential cost of capital for an asset. Their research, which only utilised well respected journals and working papers, identified 316 styles that had been researched. Additionally, they also noted a significant proliferation of research into styles during the most recent periods of their study, with 59 new styles being proposed between 2010 and 2012 (Harvey et al., 2014).

Despite this increased research and interest in styles as predictors of the cost of capital, it is important to note that this trend was not embraced by all researchers. Muller and Ward (2013), who themselves performed numerous studies into the use of styles in the South African context, predicted that any styles' correlation with returns on capital were likely to be short-lived in nature. Meanwhile, Siegel (2014) dismissed the use of styles as wholly frivolous, due to the very fact that investing based on styles projected cost of capital would influence the very outcomes that the investors wished to capitalise upon.

However, due to the significant current focus in the academic literature on styles, and the vast recent volume of styles proposed these warranted due examination. This daunting volume of styles was elegantly navigated by Muller and Ward (2013) through the development of a logical taxonomy to group styles. This taxonomy identified styles as either market based styles, financial ratio based styles, or behavioural based styles.

Market based styles looked at fundamental characteristics of firms to determine potential for future abnormal returns. These included characteristics such as the firm's industry or the size of the firm which may have correlated to a certain level of returns (Muller & Ward, 2013).

Financial ratio based styles were identified as those that relied upon historical accounting information to identify companies who were likely to provide abnormally high returns (Muller & Ward, 2013). Much of their research was based upon that of Piotroski (2000) whose research revealed that the values

of certain accounting ratios could indeed predict higher returns for the holders of a firm's shares.

Finally, behavioural based styles examined the nature of the share price behaviour over the historical term. Muller and Ward (2013) identified characteristics such as momentum in share returns and mean reversion as being such behaviours, which could lead to abnormal future share returns.

Whilst an examination of all reported styles would be highly impractical due to the vast volume, Muller and Ward (2013), suggested examining a selection of styles from at least each of the classifications to ensure that styles related to market characteristics, financial ratios and historical behaviour were all considered.

2.5.1 Market Based Styles

In Hsu and Kalesnik's (2014) research they identified market factors as being significant across numerous research studies, hence, the need to investigate a selection of these further, as performed below.

2.5.1.1 Share Sectors

In the South African financial markets the largest super-sector had remained the resources sector (Johannesburg Stock Exchange, 2015), which was unlike most developed nations' exchange constitutions. This led Muller and Ward (2013), Van Rensburg and Robertson (2003) and Ward and Muller (2012, 2015b) to identify a distinct dichotomy that existed between resource shares and non-resource shares. In general, this was evidenced by the non-resource shares outperforming the resource shares on the JSE between 1987 and 2012, with only a few brief periods during the first decade of the twenty-first century were this pattern was reversed (Muller & Ward, 2013)

Although international support for these South African observations was sparse, Faff (2001) found that Australian resource shares also historically underperformed. Australia, like South Africa, has had a disproportionately large resource contingent on the exchanges. Faff (2001) further observed that resource and non-resource shares' returns on equity responded very differently to independent variables.

As such, resource shares and non-resource shares should ideally be separated when observing their responses to independent variables, as combined tests may obscure or confound results.

2.5.1.2 Earnings Yield Ratios

Using American financial data, Fama and French (1992, 2015), found that earnings yield ratios, sometimes referred to as price-to-earnings ratios (actually the inverse of the earnings yield ratio), reflected the level of returns in relation to the market price for equity ownership. Interestingly, Fama and French (1993) initially proposed a parsimonious model that excluded any profitability measures, but in 2015 they revised their work to include a profitability measure of earnings yield which gave their model a higher degree of accuracy (Fama & French, 2015).

In the South African context, Muller and Ward (2013), Strugnell et al. (2011), and Van Rensburg and Robertson (2003) all found that earnings yield ratios were significant predictors of returns to equity capital.

This was not a surprise as Haugen and Baker (1996) found profitability measures to be strongly correlated to the cost of equity capital across both time-periods and different countries. Hence, the importance of earnings yield as a potential stylistic predictor of equity capital returns.

2.5.1.3 Company Size

Internationally, numerous researchers found that a firm's size, measured in terms of its market capitalisation, could be used as an indicator of potential returns. They found that the firm's size was inversely related to potential returns to the equity capital (Asness & Frazzini, 2013; Fama & French, 1992, 2012, 2015; Fama & MacBeth, 1973; Hsu & Kalesnik, 2014).

In the South African financial markets, this effect was also found to be prevalent in numerous studies, across several industries and time periods, with smaller firms outperforming larger firms in terms of adjusted share returns (Hoffman, 2012; Strugnell et al., 2011; Van Rensburg & Robertson, 2003).

However, the research findings were far from unanimous with Jegadeesh and Titman (2001) observing that in earlier research periods of American data, 1965 to 1989, the size effect was present (Jegadeesh & Titman, 1993), but

that it dissipated in their later research which examined data from 1990 to 1998 (Jegadeesh & Titman, 2001).

Similarly, although with more recent observations, Muller and Ward (2013) found that the South African financial market data showed a size effect was present amongst very small companies until December 2002, where after, the correlation ceased.

Harvey et al. (2014), in their meta-study, found that, on balance over all of the research they examined, a size effect did not appear to be present.

These contrasting findings suggested that additional research needed to be performed, and at the very least, verify whether or not size was indeed a factor in the South African financial environment.

2.5.2 Financial Ratio Based Styles

2.5.2.1 Market-to-Book Ratios

Fama and French (1992, 2012, 2015) had for many years been conducting research into both the CAPM and its empirical robustness, and several styles that showed evidence of stronger relationships with returns than a share's beta. During the previous 23 years, throughout which they had been identifying alternative predictors, one of the styles that had maintained its relationship with returns throughout was the market-to-book ratio, also known as the value measure of a firm. This measured the market traded price of a firm in relation to the accounting value of that firm, with firms with a lower ratio having showed consistently higher returns on their equity capital.

Other researchers, such as Asness, Moskowitz and Pedersen (2013), confirmed these findings, also using American market data as Fama and French (1992, 2012, 2015) had done.

This phenomenon was observed outside American markets too as shown by Hsu and Kalesnik (2014) who researched the relationship between styles and returns in developed nations, namely the United States of America, the United Kingdom, Europe as a whole and Japan. They too found that market-to-book ratios had a significant relationship with returns on equity.

It appeared that this anomaly was not unique to developed nations as it had also been consistently observed using South African financial data over various time periods (Muller & Ward, 2013; Strugnell et al., 2011; Van Rensburg & Robertson, 2003).

In general, there appeared to be virtually no evidence suggesting that a correlation did not exist between a low market-to-book ratio and abnormally high returns and vice versa. Admittedly, this was expected given that Harvey et al.'s (2014) meta-study identified the market-to-book variable as being very significant in relation to observed returns across the studies included in their research.

Thus any examinations of alternative predictors of the cost of equity capital would be ill-advised to not include some variation of the market-to-book ratio.

2.5.3 Behavioural Based Styles

2.5.3.1 Momentum in Share Returns

There were numerous types of momentum addressed in the research, however, Asness et al. (2013), Carhart (1997) and Yu (2012) focussed specifically on momentum in share returns. They all found that, using American financial information, past share momentum was strongly correlated with abnormally high returns to equity on those shares, and thus, that momentum could be used to predict portfolio returns.

This finding was corroborated in other developed countries' financial markets by Hsu and Kalesnik (2014) who found that share return momentum was very significant in predicting future share returns. Harvey et al. (2014), found in their meta-study that, even across the vast range of studies conducted, share return momentum remained highly significant in determining likely returns on share portfolios.

Muller and Ward (2013) and Van Rensburg (2001) also closely examined share return momentum and empirically found that past share return momentum was highly correlated to share returns in South Africa too.

However, not all authors subscribed to the notion that historical share return momentum was correlated to future potential returns, and Marks (2013)

dismissed momentum investing, whilst describing the expectation of abnormal future returns on equity, as being imprudent and irrational.

Even researchers who did find evidence of a momentum effect found that it was most significant when taking the previous 12 months' worth of returns, and that it often reversed after 12 months, with high share return momentum becoming correlated with abnormally low share returns (Jegadeesh & Titman, 2001; Moskowitz, Ooi, & Pedersen, 2012). Muller and Ward (2013), found that in the South African context similar patterns were present and that a 12 month momentum formation period, held for 3 months at a time, gave returns of 9% greater than the overall ALSI.

Forbes and Igboekwu (2015), did caution that researchers needed to understand the underlying drivers of the momentum, as phenomena such as analyst' forecasts that caused momentum could distort results. Nevertheless, even without the record of the causes of momentum, momentum remained a factor worth investigating for correlations with abnormal returns on equity capital.

A point worth noting is that while the styles were discussed individually their effects may have been impacted by other styles that were simultaneously investigated in the research. Field (2013) elaborated on the potentially significant interaction of so called independent variables, or styles in this context, which could either diminish or augment the observed impacts, but that the possibility of confounding was significant.

International research, such as that by Asness and Frazzini (2013), Asness et al. (2013) Fama and French (1992, 1993, 2004, 2012, 2015), actually researched the style impacts in the presence of other styles. Similarly, Muller and Ward (2013), Van Rensburg (2001), Van Rensburg and Robertson (2003) and Ward and Muller (2012) looked at multi-style models in the South African context, demonstrating that styles were seldom used as stand-alone predictors of returns, yet their potential interactions needed to be recognised.

2.6 Conclusions Drawn from the Literature Review

As had been highlighted, the CAPM formed a critical foundation to the academic application of costing equity capital. The CAPM had shown remarkable longevity in its use by academia since being postulated in the mid-1960s. Furthermore, Strydom and Charteris (2013) empirically demonstrated how the CAPM, with some variations, still applied to the South African financial markets within recent times.

The number variations, some of which were applied by Strydom and Charteris (2013), were numerous, but the most critical of these appeared to be the Black's CAPM (Black, 1972), the periods over which the beta was examined and adjustments made to compensate for potential illiquidity impacts upon the beta.

The first of these adjustments, the Black's CAPM (Black, 1972), removed the dependency on a risk free rate proxy such as a treasury bill or treasury bond, through rather producing a minimum variance efficient zero-beta portfolio and using its historical returns as the risk free rate. This typically provided higher risk free rates than the traditional proxies.

Despite these potential variations and improvements to the CAPM, and the subsequent wider range of projected equity capital returns that these provided, criticism of the CAPM had become widespread. A plethora of international researchers had empirically found results opposing the CAPM, since Fama & French (1992) first questioned the CAPM through to their most recent research in 2015.

Even in South Africa, the CAPM had been unable to avoid harsh empirical opprobrium since the research by Van Rensburg (2001) right through to the most recent research by Ward and Muller (2015b), which actually showed that there was an inverse relationship between beta and the implied cost of equity capital.

Thus, the question still remained about whether or not the CAPM was an accurate representation of the South African financial markets' returns for equity capital. Strydom and Charteris (2013) contended that it was and Ward and Muller (2012, 2015b) directly opposed this assertion by contending that it was an empirically poor fit. Hence, there was a need to conduct clarifying

research on the CAPM's applicability, with all of its variations, to the South African financial markets.

If, as suggested by Strugnell et al. (2011), Van Rensburg (2001), Van Rensburg and Robertson (2003) and Ward and Muller (2012, 2015b), the CAPM did not apply to the South African market it would have been prudent to have investigated some other factors which could have affected the cost of equity.

Based on the research there were 316 styles which could have offered alternative options for calculating the cost of equity capital (Harvey et al., 2014). However, five styles were selected, which the research suggested held potential significance both internationally and within South Africa, although unanimous empirical support for these styles was not a prerequisite for selection. These likely styles which appeared to hold possible predictive potential, even though they still required further testing, were share sectors, earnings yield ratios, company size, market-to-book ratios and share return momentum.

Although the research into these styles appeared extensive, both internationally and in South Africa, much of the South African research found broad visual trends, but stopped short of running statistical analyses to test for the statistical significance of the findings. Furthermore, very little research appeared to offer up a useable alternative pricing model. In fact, no research was found which comprehensively proffered a model with which a specific firm's historical information could be populated to generate the projected cost of equity capital for South African firms, so this remained a potential gap in the research to date.

Chapter 3 Hypotheses

The numerous variants of the CAPM as well as its components and time horizons, as discussed in Chapter 2, gave rise to numerous hypotheses. For ease of analysis these were grouped into 3 distinct sections, namely, tests of the original CAPM, tests of Black's CAPM, and tests of alternative pricing models.

3.1 Tests of the Original CAPM

The null hypothesis stated that the original CAPM held true for the South African financial market. Thus, that expected returns on an asset, or portfolio of assets, could be predicted through analysing the interaction between the risk free rate (R_f), given by a standard treasury bill, the relative risk of the asset, or portfolio of assets, of interest (β_i) and the expected return on the portfolio of all the shares in the market ($E(\tilde{R}_m)$). The alternative hypothesis stated that the CAPM did not act as a statistically significant predictor of expected returns for the South African market. For this specific test a 24 month time horizon was utilised to calculate the betas.

$$H1a_0: E(\tilde{R}_i) = R_f + \beta_i[E(\tilde{R}_m) - R_f]$$

$$H1a_A: E(\tilde{R}_i) \neq R_f + \beta_i[E(\tilde{R}_m) - R_f]$$

The next null hypothesis was identical to that depicted in $H1a_0$, however, the 24 month time horizon for beta calculations was replaced by a 60 month time horizon to ensure beta look-back periods were not skewing the results. This followed a comparable method to that used by Ward and Muller (2012). The alternative hypothesis was similar to $H1a_A$, except that its time horizon was also increased to 60 months.

$$H1b_0: E(\tilde{R}_i) = R_f + \beta_i[E(\tilde{R}_m) - R_f]$$

$$H1b_A: E(\tilde{R}_i) \neq R_f + \beta_i[E(\tilde{R}_m) - R_f]$$

The next null hypothesis was the same as $H1a_0$, however, in $H1a_0$ the beta calculation made the assumption of frequent trading of the financial assets under consideration, however, to compensate for possible infrequent trading the Dimson' beta calculation was performed (Dimson, 1979). The time horizon remained at 24 months for the beta calculations. This technique was also applied by Ward and Muller (2012), however, they did note that infrequent trading was unlikely to be a hindrance for shares on the Johannesburg Stock Exchange's All Share index, but it was nonetheless deemed advisable to account for infrequent trading. The alternative hypothesis was the same as $H1a_A$, simply adjusted to utilise the Dimson' beta calculation over a 24 month time horizon.

$$H1c_0: E(\tilde{R}_i) = R_f + \beta_i[E(\tilde{R}_m) - R_f]$$

$$H1c_A: E(\tilde{R}_i) \neq R_f + \beta_i[E(\tilde{R}_m) - R_f]$$

The final null hypothesis for the first category of testing was the same as $H1c_0$, immediately above, except that a 60 month time horizon was utilised to account for differences in beta calculations introduced through different time horizons. Naturally, the alternative hypothesis was identical to $H1c_A$, except that its beta time horizon was adjusted to 60 months too.

$$H1d_0: E(\tilde{R}_i) = R_f + \beta_i[E(\tilde{R}_m) - R_f]$$

$$H1d_A: E(\tilde{R}_i) \neq R_f + \beta_i[E(\tilde{R}_m) - R_f]$$

3.2 Tests of Black's CAPM

As mentioned previously, Black (1972) proposed a variant on the original CAPM, where the model was no longer reliant on the use of treasury bills as a proxy for the risk free rate, but rather utilised a minimum variance zero-beta portfolio as the proxy. In the same vein, the first null hypothesis in this section of hypotheses stated that Black's CAPM held true for the South African financial market. Thus, that expected returns on an asset, or portfolio of assets, could be predicted through analysing the interaction between the

expected returns on a zero-beta portfolio ($E(\tilde{R}_z)$), the relative risk of the asset, or portfolio of assets, of interest (β_i) and the expected return on the portfolio of all the shares in the market ($E(\tilde{R}_m)$). The alternative hypothesis stated that Black's CAPM did not act as a reliable predictor of expected returns for the South African market. Strydom and Charteris (2013) made extensive use of the Black's CAPM in their paper. For this specific test a 24 month time horizon was used to calculate the betas.

$$H2a_0: E(\tilde{R}_i) = E(\tilde{R}_z) + \beta_i[E(\tilde{R}_m) - E(\tilde{R}_z)]$$

$$H2a_A: E(\tilde{R}_i) \neq E(\tilde{R}_z) + \beta_i[E(\tilde{R}_m) - E(\tilde{R}_z)]$$

The next null hypothesis was identical to that depicted in $H2a_0$, however, the 24 month time horizon for beta calculations was replaced by a 60 month time horizon. The alternative hypothesis was similar to $H2a_A$, except that its time horizon was also increased to 60 months.

$$H2b_0: E(\tilde{R}_i) = E(\tilde{R}_z) + \beta_i[E(\tilde{R}_m) - E(\tilde{R}_z)]$$

$$H2b_A: E(\tilde{R}_i) \neq E(\tilde{R}_z) + \beta_i[E(\tilde{R}_m) - E(\tilde{R}_z)]$$

The next null hypothesis was the same as $H2a_0$, except that the Dimson' beta calculation was performed. The time horizon remained at 24 months for the beta calculations. The alternative hypothesis was the same as $H2a_A$, simply adjusted to utilise the Dimson' beta calculation over a 24 month time horizon.

$$H2c_0: E(\tilde{R}_i) = E(\tilde{R}_z) + \beta_i[E(\tilde{R}_m) - E(\tilde{R}_z)]$$

$$H2c_A: E(\tilde{R}_i) \neq E(\tilde{R}_z) + \beta_i[E(\tilde{R}_m) - E(\tilde{R}_z)]$$

The final null hypothesis for this category of testing was the same as $H2c_0$, immediately above, except that a 60 month time horizon was utilised to account for differences in beta calculations introduced through dissimilar time

horizons. Naturally, the alternative hypothesis was identical to $H2c_A$, except that its beta time horizon was adjusted to 60 months too.

$$H2d_0: E(\tilde{R}_i) = E(\tilde{R}_Z) + \beta_i[E(\tilde{R}_m) - E(\tilde{R}_Z)]$$

$$H2d_A: E(\tilde{R}_i) \neq E(\tilde{R}_Z) + \beta_i[E(\tilde{R}_m) - E(\tilde{R}_Z)]$$

3.3 Tests of Alternative Pricing Models

Finally, if, as suggested as a possibility in the review of the relevant theory and literature, none of the variations of the CAPM proved applicable to the South African market, a test of an alternative pricing model would have been required. Thus, a test of a model containing a selection of the identified potential styles that could impact the cost of equity was required.

To test this, it was essential that the selected styles be combined in such a manner as to provide each share with a combined score, which became known as the optimised returns score (ORS), at any point in the share's existence. However, as these individual current scores would fluctuate introducing significant volatility into the cost of equity predictions, it was necessary to view the share's historical ORSs too to provide a more comprehensive and reflective view of the predicted cost of equity.

These ORSs would then be classified, based upon which quintile they fell into, in relation to all of the scores of all of the top 160 shares under examination. Again the use of quintiles in favour of specific share rankings was employed to reduce share specific volatility. Based upon the amount of time a given share spent in each quintile of the optimised returns score, it should have been possible to form a prediction of the share's cost of equity capital.

Furthermore, due to the dichotomy identified by Muller and Ward (2013), Van Rensburg and Robertson (2003) and Ward and Muller (2012, 2015b), there would need to be two hypotheses tested depending on whether the share was classified as a resource or a non-resource share.

Thus, Equation 3 was formed:

Equation 3: Alternative Pricing Model

$$E(\tilde{R}_i) = b_0 + b_1R_{Q1} + b_2R_{Q2} + b_3R_{Q3} + b_4R_{Q4} + b_5R_{Q5}$$

where,

$E(\tilde{R}_i)$ is the expected return for share i ($i = 1$ to 160);

b_0 is the constant return for share i ($i = 1$ to 160);

b_1 is the amount of time the share had spent in the ORS Quintile 1;

R_{Q1} is the calculated constant multiplier associated with the ORS for Quintile 1;

b_2 is the amount of time the share had spent in the ORS Quintile 2;

R_{Q2} is the calculated constant multiplier associated with the ORS for Quintile 2;

b_3 is the amount of time the share has spent in the ORS Quintile 3;

R_{Q3} is the calculated constant multiplier associated with the ORS for Quintile 3;

b_4 is the amount of time the share has spent in the ORS Quintile 4;

R_{Q4} is the calculated constant multiplier associated with the ORS for Quintile 4;

b_5 is the amount of time the share has spent in the ORS Quintile 5;

R_{Q5} is the calculated constant multiplier associated with the ORS for Quintile 5.

As such, the null hypotheses stated that no time spent in any quintile had any effect i.e. that each of the quintile return constants ($R_{Q\dots}$) was equal to zero, hence, rendering that quintile's impact statistically insignificant. The alternative hypotheses stated that at least one of the quintile returns had an effect on the expected returns of a specific firm's equity. This ultimately led to the following hypotheses.

For non-resource shares

$$H3a_0: R_{Q1} = R_{Q2} = R_{Q3} = R_{Q4} = R_{Q5} = 0$$

H3a_A: At least one R_Q is not zero

And for resource shares

$$H3b_0: R_{Q1} = R_{Q2} = R_{Q3} = R_{Q4} = R_{Q5} = 0$$

H3b_A: At least one R_Q is not zero

Chapter 4 Research Methodology

4.1 Choice of methodology

The research was designed to be quantitative and causal in nature, as would be expected in a financial research paper, and was also applied in the recent papers by Strydom and Charteris (2013) and Ward and Muller (2012). Due to the time based nature of the financial data, where appropriate, these were segmented to facilitate time series analysis, both graphically and statistically, in an analogous fashion to that employed by Muller and Ward (2013).

Furthermore, this approach was particularly appropriate given the observation by Muller and Ward (2013) that correlations with abnormal returns on equity capital tended to be short-lived, and hence observing returns over shorter time periods was judicious.

4.2 Population

The population to which this research would ideally apply is to any South African firm that needed to conduct financial investment planning. Whilst this would typically include all firms, not all firms would have access to the data needed to populate the CAPM or any alternative models developed, so these firms would thus realistically have to be excluded from the population.

Thus, the effective population, to which the research would be applicable, was South African companies listed on the JSE, who had sufficient market capitalisation to be included in the JSE's ALSI. It should also be noted that this applied to any firm who at any stage between 1985 and 2014 had sufficient market capitalisation, irrespective of their eventual state. Thus, survivor bias was virtually eliminated through the use of a time series. A potential introduction of survivor bias was seen in the formulation of the minimum variance zero-beta portfolios where the shares included needed to be in existence for the entire time period under investigation. The number of shares utilised in each case were reported in the applicable tables in Chapter 4. Another source of survivorship bias was fact that only shares that were still listed at the end of 31 December 2014 were included in the building of the

alternative model, as the future price of unlisted shares was deemed irrelevant according to the purpose of this study. The use of the Dimson' beta calculation also ensured that having highly traded liquid shares was not a prerequisite for forming part of the population.

4.3 Unit of Analysis

The appreciation or depreciation of individual share value, including adjustments for unbundling, mergers, share splits and dividend pay-outs, was the primary unit of analysis against which the hypotheses were tested. However, during the testing these individual shares were grouped into virtual portfolios to control for individual share return volatility, similar to the technique employed by Ward and Muller (2012). Furthermore, again in line with the approach of Ward and Muller (2012), the portfolios were rebalanced each quarter to ensure the portfolio remained reflective of the specific characteristics under investigation.

The virtual portfolio share returns were analysed in terms of their percentage change as done by Strydom and Charteris (2013) and Ward and Muller (2012, 2015b), and then viewed in terms of their relative performance to the overall market, in a similar approach to that employed by Forbes and Igboekwu (2015). This facilitated the effective nullification of market wide macroeconomic fluctuations, such as the dot com bubble in the last decade of the twentieth century and the global financial crisis in the first decade of the twenty-first century, which may have skewed the results of the various time periods under review.

It should be noted that hypothetical transaction costs involved in the construction, and rebalancing, of the virtual portfolios were ignored, based on the rationale employed by Ward and Muller (2012), that transaction costs would be approximately equal in each of the portfolios, so would not materially affect the outcome of the research.

4.4 Sampling Method and Size

The sample used, being the top 160 shares on the JSE's ALSI, between 31 December 1984 and 31 December 2014, based on market capitalisation, ensured that 99% of South Africa's market capitalisation (Johannesburg Stock Exchange, 2015; Ward & Muller, 2012) was accounted for. The quantitative, highly mechanised nature of the analysis, combined with the freely available information of all shares within the population meant that a judgment sampling technique was both possible and appropriate (Zikmund, Babin, Carr, & Griffin, 2012). This sampling method was utilised by Ward and Muller (2012), whereas (Strydom & Charteris, 2013) used a census sampling technique by collecting data from all of the listed shares on the JSE ALSI over the period under review.

Ward and Muller (2015b) actually pointed out that by selecting all of the shares and affording them all equal weighting, Strydom and Charteris (2013) had attached equal statistical relevance to shares with small market capitalisation and that were likely to be highly illiquid.

The period over which the sample was analysed, namely from the beginning of 1985 to the end of 2014, included the time periods analysed by both Ward and Muller (2012) and Strydom and Charteris (2013).

As of the 31st of March 2015, there were 171 constituents listed on the JSE ALSI (Johannesburg Stock Exchange, 2015), however, this number would fluctuate over time as listings, delistings and mergers changed the absolute number of firms' shares included in the ALSI. However, it did provide an approximate indication of the population size between 1985 and 2014, so the sample size of 160 firms did not appear markedly different from the population size.

The selection of 160 shares also lent itself well to the selection of equally sized virtual portfolios throughout all periods that were examined, in the same manner as that employed by Muller and Ward (2013) and Ward and Muller (2012).

4.5 Measurement Instrument

The primary measurement instrument used was the Ward and Muller (2015a) style engine, which contained data that had been collected over numerous years to reflect share returns' appreciations and depreciations. Furthermore, it had adjusted data, based on Sharenet information, to accommodate unbundlings, mergers, share splits and dividend pay-outs that had occurred. Historical recordings of share prices were also saved within the dataset as Google Finance did not contain information for shares that had been delisted from the JSE. This style engine was constructed using Microsoft Excel, including the associated Visual Basic for Applications (VBA) programming code, and Microsoft Access. Excel was utilised to perform further processing and visualising of the data under review, again making extensive use of VBA code procedures, and IBM SPSS was used for the statistical analyses.

4.6 Data Gathering Process

As mentioned, the Ward and Muller (2015a) style engine was used which was prepopulated with appropriately amended financial data, so no additional data gathering was required.

4.7 Analysis Approach

The analysis took the form of four major examinations, although only three of these were reflected in sets of hypotheses, which progressed from an examination of the most basic traditional CAPM, in numerous configurations, through to an eventual multivariate alternative model. The approach and specific tests employed are discussed in the sections below.

4.7.1 Analysis of the Original CAPM

The CAPM, reproduced in Equation 4 below for convenience, contains numerous variables such as the risk free rate, R_f . For the first selection of tests, R_f was defined according to convention as the average standard South African treasury bill rate that prevailed during the time period analysed. This

was the same approach followed by previous researchers such as Fama and MacBeth (1973), Nikolaos (2009) and Ward and Muller (2012) amongst others.

Equation 4: The Original CAPM

$$E(\tilde{R}_i) = R_f + \beta_i[E(\tilde{R}_m) - R_f]$$

In Equation 4,

$E(\tilde{R}_i)$ is the expected return on an asset i ;

R_f is the return on a risk-free asset, typically a treasury bill or bond rate;

β_i is the risk associated with asset i i.e. its market sensitivity;

$E(\tilde{R}_m)$ is the return on the portfolio that consists of all of the assets within the market (Black, 1972).

The market return, represented by $E(\tilde{R}_m)$, was calculated for each of the periods under review, whilst the beta, β_i , was also calculated according to the beta look-back period under review, as expanded upon in the detailed test descriptions discussed below.

The chief difference between the analyses conducted as part of the tests of the original CAPM was the look-back period for the betas and the specific calculation method of the beta.

4.7.1.1 Tests of Hypothesis $H1a_0$

Firstly, the equation was tested with a 24 month beta where 24 months of data were used to create the betas using the standard beta equation shown in Equation 5 below, which measured the sensitivity of the expected excess asset returns to the excess market returns.

Equation 5: The Standard Beta Formula

$$\beta_i = \frac{Cov(R_i, R_m)}{Var(R_m)}$$

Hence, for the 24 month beta, the data from the beginning of 1985 through to the end of 1986 was utilised to calculate the first set of share's betas. Then to test the expected returns according to the original CAPM against actual out-of-sample returns, the subsequent 24 months of results were examined, thus making the time period under examination 48 months long, with the first period being from the beginning of 1985 to the end of 1988. The next time period for calculating the betas then commenced at the beginning of 1987 and so on until a total of 14 time periods for examination were achieved.

Within each time period each of the 160 shares had both an actual percentage return and a projected percentage return as based upon the traditional CAPM using a 24 month beta. These returns were not rebased to measure excess returns over the market as this would have been needless as the shares were compared against each other, so rebasing according to the market returns was not required.

The fit of the results was graphically observed by plotting the actual results against the projected results. As the results were expected to be correlated, if the CAPM predictions were accurate, the results would have formed a 45 degree line to show positive correlation if it did indeed exist.

To statistically test if the actual returns and projected returns were statistically significantly similar, hence, proving null hypothesis $H1a_0$, a paired-samples t-test was conducted to test for significance at the 95% confidence level, as were all statistical tests in this research. This only allowed for a 5% chance of a type I error (Field, 2013), using the identical confidence level as in the research conducted by Hsu and Kalesnik (2014), Lazar and Yaseer (2010) and Van Rensburg and Robertson (2003). The paired t-test was appropriate due to the normally distributed nature of the differences between the two sets of results, and the fact that the same shares were being compared against each other.

The mere fact that share returns had historically been volatile, and potentially not normally distributed was not a hindrance to using the paired-samples t-test, as only the differences between the sampled scores needed to be normally distributed (Field, 2013). The central limit theorem which stated that a sample could be assumed to be normally distributed if there were more than

30 samples meant that normality could be safely assumed in this case where 160 shares were sampled (Field, 2013).

Field (2013), also highlighted the fact that paired-sample t-tests are more powerful than independent t-tests. This is due to the reduction of the unsystematic variance, making it easier to observe differences that come about based on the different treatment of the data, or, as in this research, the predictive use of the CAPM versus the actual results.

This t-testing was performed for each of the 14 time periods, and for the entire time series, to establish the CAPM's applicability, as claimed by null hypothesis $H1a_0$, and determine if this applicability was present throughout the entire time series or was an intermittent phenomenon.

4.7.1.2 Tests of Hypothesis $H1b_0$

The next series of tests that were conducted were exactly the same as for $H1a_0$, as described above, however, the look-back period for the beta was increased to a 60 month period.

Hence, the first time period under review for the purposes of calculating the beta was from the commencement of 1985 until the closure of 1989, and the out-of-sample period against which it was tested was from 1990 until the end of 1994. In total the data were divided into 5 time series which were each examined, based on their percentage returns, graphically and statistically in the same manner as was employed for the tests for hypothesis $H1a_0$, as described above.

4.7.1.3 Tests of Hypothesis $H1c_0$

The tests applied for the testing of hypothesis $H1c_0$, were largely the same as those used for hypothesis $H1a_0$, as described above, as they both utilised 24 month look-back periods for their betas. However, for hypothesis $H1c_0$, the Dimson' beta calculation was used, to ensure that illiquidity in a share's trading did not distort the beta scores. The Dimson' beta calculation was reproduced in Equation 6, below, for convenience. This equation was used by Ward and Muller (2012), although they did also note that while the test was prudent, illiquidity was unlikely to be of major concern amongst the top 160 shares on the JSE ALSI.

Equation 6: Dimson's Aggregated Coefficients Model

$$r_{i,t} = \hat{\alpha}_i + \sum_{k=-n}^1 \hat{\beta}_{i,k} \cdot r_{m,t+k} + \epsilon_{i,t}$$

In Equation 6,

$r_{i,t}$ is the return on share i at time t ;

$r_{m,t+k}$ is the market return at time $t + k$;

$\hat{\beta}_{i,k}$ is the estimated beta for share i at a lag of k periods in the multiple regression;

$k = -n$ is the selected number of lag periods to include in the equation.

$\epsilon_{i,t}$ captures the error

Ward and Muller (2012) utilised four lag periods, and this research used the same number of lag periods where possible, however, where this duration of data was not available, a minimum of 24 months of lag was included. Failing this, the results were excluded from the analysis as per the method employed by Ward and Muller (2012).

Thereafter, the same graphical and statistical examinations of the results were performed to test the applicability of the CAPM, utilising the Dimson' 24 month beta, at a 95% confidence level.

4.7.1.4 Tests of Hypothesis $H1d_0$

Hypothesis $H1d_0$ was palpably the same as hypothesis $H1c_0$, except that the 24 month look-back period was replaced with a 60 month look-back period, whilst the Dimson' formula was still employed using four lag periods where sufficient information was available. Where sufficient data was not available the same guidance of using no less than 24 months of data was employed, otherwise the share was discarded from the dataset for that time period, as done by Ward and Muller (2012).

Thereafter, the same graphical and statistical evaluations were performed as with the preceding three hypotheses.

4.7.2 Analysis of Black's CAPM

For each of the hypotheses relating to the Black's CAPM the minimum variance zero-beta portfolio returns were calculated to replace the risk free proxy of the original CAPM (Black, 1972). This brought about the formula seen in Equation 7, reproduced below for reference purposes.

Equation 7: The Black's CAPM

$$E(\tilde{R}_i) = E(\tilde{R}_z) + \beta_i[E(\tilde{R}_m) - E(\tilde{R}_z)]$$

Where all variables remained the same as those used in the original CAPM, apart from $E(\tilde{R}_z)$ which represented the expected return of the efficient minimum variance zero-beta portfolio, which replaced the risk free return, as it represented the achievable return through nullifying any exposure to market fluctuations (Black, 1972).

The actual calculation of this portfolio made use of the equation as seen below in Equation 8.

Equation 8: The Zero-Beta Portfolio

$$\beta = \frac{w \cdot cov \cdot B^T}{B \cdot cov \cdot B^T}$$

In Equation 8,

β is the zero-beta efficient frontier

w is the matrix of the weights of each share in the portfolio

B is the matrix of the weights of the benchmark at the specific time, in this case the JSE ALSI.

cov is the covariance matrix produced (Ward & Muller, 2015b)

To be classified as an efficient frontier the portfolio was optimised to ensure that no greater returns could be achieved for the given level of variance of the portfolio.

Furthermore, other constraints were applied such as forcing the sum of the weights of the shares to be equal to 1. This was not strictly speaking required as it may have been assumed that the short sold shares could fund the long held shares, but both Strydom and Charteris (2013) and Ward and Muller (2015b) applied this constraint, so in the interests of comparability this was applied.

One drawback, as encountered by Ward and Muller (2015b), was that by producing a portfolio based on the entire period's data all shares that did not exist for the entire period under evaluation had to be excluded due to the usage of a covariance matrix in their calculations. This considerably reduced the size of the matrix, reducing its reliability, and introduced significant survivor bias. To overcome this they found the midpoint of their time range and built a matrix based on all of the shares that were in existence at that point. However, as this study used zero-beta portfolio returns, based on at most 60 months of data, this fixing of the portfolio at a specific date was deemed unnecessary as the attrition of shares would have been far smaller than the Ward and Muller' (2015b) research where they used the entire time period from 1984 until 2015 to calculate their zero-beta portfolio.

This still potentially allowed some survivorship bias as only shares that had existed for the duration of the look-back period were included, and the few that had ceased to exist were excluded in the same manner as that employed by Ward and Muller (2015b). Although it should be noted that those shares that had ceased to exist within the exchange, especially if the underlying firm had ceased to exist, would have likely had large negative betas and poor returns, so would have been unlikely to have been included in an efficient zero-beta portfolio. Interestingly, Strydom and Charteris (2013) did not disclose the method they utilised to address the problem of survivorship bias, although it was unlikely to be as large an issue for them as they made use of a far smaller time series from 1993 to 2008.

The primary difference between the tested hypotheses, that involved the Black's CAPM, related to the beta look-back periods employed and the way that illiquidity was addressed, however, these are further elaborated on below.

4.7.2.1 Tests of Hypothesis $H2a_0$

In a similar manner to that employed for hypothesis $H1a_0$'s testing each look-back period was 24 months in duration, resulting in there also being 14 time periods that were evaluated. For each of these time periods the shares that had existed for the entire duration of the period were identified and the efficient minimum variance zero-beta portfolio was calculated using these.

As with hypothesis $H1a_0$, each of the shares under evaluation had a predicted return based on the Black's CAPM using a 24 month beta, as well as the actual return for the 24 month out-of-sample evaluation period. A graphical examination was performed to establish whether the actual and predicted results appeared positively correlated.

Thereafter, a paired t-test was undertaken, as with hypothesis $H1a_0$, and was subject to the same confidence levels of 95%, and strengths and weaknesses as discussed under that hypothesis. These tests were used to establish whether hypothesis $H2a_0$ was statistically significant, and whether the Black's CAPM, using a 24 month beta, was a statistically significant predictor of the returns on shares over each time period and over the entire research time range.

4.7.2.2 Tests of Hypothesis $H2b_0$

The methodology for testing hypothesis $H2b_0$ was not dissimilar from that used to test hypothesis $H2a_0$. The only difference being that the look-back period for determining the beta was increased to 60 months, subsequently reducing the evaluation to five time series.

The method for calculating the zero-beta efficient minimum variance portfolio remained the same, except that the previous 60 months of data were utilised to calculate the minimum variance zero-beta portfolio returns for the succeeding 60 months.

Thereafter, the same graphical and statistical analysis was employed to test the significance of the null hypothesis, for each of the time periods and the overall time period as a whole.

4.7.2.3 Tests of Hypothesis $H2c_0$

The tests performed for hypothesis $H2c_0$ were very similar to those performed for hypothesis $H1c_0$, as a 24 month Dimson' beta was used. This beta was subsequent to the same controls as in the tests on $H1c_0$, as a minimum of 24 months of data had to exist for the lag periods, and where possible 4 lag periods were used.

The only difference was that the minimum variance zero-beta portfolio was calculated in the same manner as had been used for hypothesis $H2a_0$, before the graphical and statistical t-testing of the hypothesis was conducted, using the same criteria of 95% confidence.

4.7.2.4 Tests of Hypothesis $H2d_0$

The examination of hypothesis $H2d_0$ was the same as for $H2c_0$, barring the use of a Dimson' beta that used a 60 month look-back period. The same controls existed as with hypotheses $H1c_0$, $H1d_0$ and $H2c_0$ to ensure sufficient lag periods were used to address any potential trading illiquidity.

Thereafter, the same graphical and statistical examinations were performed to test the null hypothesis that stated that the Black's CAPM using a 60 month Dimson' beta was an accurate predictor of actual returns.

4.7.3 Consolidation of CAPM Findings

Given the general findings against the use of CAPM, it was decided that, although not strictly required for the testing of one of the hypotheses, that there was benefit to be had by consolidating the findings through examining the key relationship underpinning the CAPM. This relationship, as shown in the literature review, was a positive correlation between risk, represented by the beta, and the returns on the equity capital (Fraser et al., 2004; Harford, 2014; Hearn & Piesse, 2009; Kansas, 2010; Lintner, 1965; Markowitz, 1952; Mossin, 1966; Nikolaos, 2009; Sharpe, 1964; Strydom & Charteris, 2013).

To test this relationship visually, the shares were ranked according to their conventional 60 month look-back betas and divided into quintiles to simulate virtual portfolios. The ranking and subsequent tests could have been conducted on any of the beta variations, however, for the purposes of

demonstrating the relationship between beta and returns the 60 month look-back beta was deemed sufficient.

These quintiles were rebased at the end of every quarter to ensure that the correct shares, according to their updated betas, were allocated to the appropriate virtual portfolios as done by Muller and Ward (2013) and Ward and Muller (2012).

To ensure that the time series perspective was still visible, a line known as a price relative was added to show how the highest beta ranked portfolio performed in relation to the lowest beta ranked portfolio over time to show any relationships and how they changed over time (Muller & Ward, 2013; Ward & Muller, 2012).

To statistically test the relationship, an ANOVA was performed for the beta ranked results, based on quarterly returns relative to the market's performance. Being a robust statistical test the ANOVA could handle non-normal distributions, although homogeneity of variances was still tested using the Levene's test. Where the test was failed, indicating heterogeneity of variances, the Welch's F-test was deemed a suitable replacement for the ANOVA (Field, 2013). Furthermore, where the sample group sizes were equal, as ensured in this research by the use of equal quintiles, the assumption of homogeneity of variances was less critical (Field, 2013).

Through the use of the F statistic from the ANOVA, or Welch test where appropriate, the direction of variation was determined (Field, 2013) to test whether, statistically, there was a relationship between the betas of the portfolios and the returns as suggested by the positive relationship claimed in the CAPM.

Thereafter, where a relationship was detected, a Tukey post hoc test was conducted to determine whether the relationships observed were statistically significant at the 95% confidence level, or not (Field, 2013). Post hoc tests were observed to generally be robust where the sample group sizes were equal (Field, 2013), such as with the use of quintiles in this research, ensuring increased confidence in the outputs. This allowed for the consolidation of the findings around the relationship between risk, as measured by the conventional 60 month look-back beta, and returns.

4.7.4 Analysis of Alternative Pricing Models

Given that both the original CAPM and Black's CAPM failed to demonstrate an irrefutable correlation with the actual equity capital returns, further analysis was performed.

4.7.4.1 Individual Style Analyses

The initial step was to evaluate each of the styles, identified in Chapter 2, individually by ranking the shares according to their score on the style and then dividing the shares into quintiles of virtual portfolios, in a similar fashion to that employed by Muller and Ward (2013). The sector style did not lend itself to ranking and as such the shares were simply divided into resource shares and non-resource shares.

The virtual portfolios were rebalanced at the end of each quarter to ensure that the portfolios stayed representative of the style under evaluation. A method that was also employed by Muller and Ward (2013) and Ward and Muller (2012).

For each of these individual style based portfolios the cumulative returns were plotted over the entire time period to give a graphical impression of any potential correlation in returns and the style being examined. Where after, the same style was statistically analysed using an ANOVA, or Welch test if appropriate, with the post hoc Tukey test where required, as recommended by Field (2013), to establish if a significant effect was present. For these tests, the quarterly market relative returns were used to remove month-to-month volatility, and the systemic market volatility.

The only exception to this was on the sector style where the shares were divided into either resource or non-resource shares. The cumulative returns of these virtual portfolios were then graphically plotted, and an independent t-test was performed on the market relative quarterly returns to test for significant differences.

The concern with an analysis, such as the independent t-test, would be to determine if the returns were normally distributed and if there was homogeneity of variance. The test for normality was not required due to the

central limit theorem and the fact that the sample included 160 shares, greater than the cut-off of 30, beyond which normality could be assumed (Field, 2013).

To test for homogeneity of variance, the Levene's test was performed and the appropriate set of results was then analysed dependent upon the passing of the test.

It should be noted that these individual evaluations were conducted to merely be indicative of individual style effects. Field (2013) stated that whilst certain independent variables may show a certain level of correlation with the dependent variable, in this case market relative quarterly share returns, when combined with another variable, or variables, an altered effect may well be observed due to interaction between the variables.

4.7.4.2 Construction of the ORS

To commence construction of the optimised returns score (ORS) the first step was to split the shares into resource shares and non-resource shares. This allowed each group to be treated and optimised separately due to their dichotomous nature.

Thereafter, each individual share had its market-to-book ratio, earnings yield, market capitalisation and 12 month momentum calculated at the first date in the time series, namely the 31st of December 1984 for those shares in existence. These values were recalculated every quarter. Each share was then ranked based on each of the individual styles separately, and a percentage was assigned to the share based on where it classified in relation to the other shares in the market. By way of example the best share in a particular style would receive a 0% rating and the worst share would receive a 100% rating. This relative ranking effectively removed spurious systemic fluctuations based on overall market performance.

These scores were then added together to generate a descriptive score for each share, based upon which quintiles were formed which were then plotted to graphically observe how the various quintiles performed over the time period. It should be noted that the quintiles were rebalanced quarterly to ensure the constituent shares remained appropriately represented.

However, this result assumed that the styles carried an equal weight in determining the returns for a share, or portfolio of shares. Therefore, to more appropriately apportion weights to the styles a single style's weight was fixed- in the case of this research momentum was fixed due to its strong individual correlation to returns. Thereafter, an optimisation engine, coded in VBA for Excel, was run to simulate returns for quintile 1 based on various weightings for the selected styles, and an optimal weighting was then identified for each style for both resources and non-resources. Given these optimised weightings, the quintiles were reformed with each share's new ORS and again graphically observed. These were then tested for significance through the use of an ANOVA, or Welch test if required, with a Tukey post hoc test.

Following this, each share had its overall returns and the percentage of time spent in each ORS quintile recorded. All shares that had ceased to exist were removed, as calculating future returns for shares no longer in existence was nonsensical. Furthermore, those shares which had been in existence for less than four quarters were also removed, to prevent spurious results due to insufficient time in the market to generate a meaningful performance history. Using this data a multiple regression was run for each of the resources and non-resources groups.

For the multiple regressions, a forced entry process was utilised, as Field (2013) found it to be the preferred method due to its imperviousness to random variation in the data, and statistical significance was tested for each of these at a 95% level. The time percentages per quintile were entered into the multiple regression model in descending order of their individual explanatory ability, based on the R^2 . The resulting model with the highest R^2 was deemed best due to its explanatory power. Those time percentages spent in a specific quintile that proved to be non-significant were removed from the model, and the model was rerun until all of the included time percentages per quintile were statistically significant.

To detect the presence of multicollinearity between the independent time percentage variables the variance inflation factor (VIF) and tolerance statistics were observed, as calculated by IBM SPSS, and recommended by Field (2013). Multicollinearity was deemed to be present if the VIF was greater than 10 or tolerance was less than 0.2 (Field, 2013).

Unfortunately, as stated by Field (2013), there was no real solution to remove the multicollinearity, as even the removal of an independent variable was inappropriate as it could not be known which of the variables should be removed. As such, in this research where multicollinearity was detected, the intention was to merely note its presence as a potential contributor to unreliability in the model.

Another potential concern that was identified prior to running the multiple regressions was the issue of sample size. Field (2013) stated that the size of the effect that was expected to be observed determined the required size of the sample. Field (2013) classified large effects as those having an R^2 of 0.26 or higher, medium as having an R^2 of at least 0.13 and a small effect as having an R^2 of less than 0.02. Through the interpretation of Field's (2013) graphs, shown below in Figure 1 through Figure 3, it can be seen that with five predictors to detect a large effect a sample size of 43 was required, for a medium effect 92 and for a small effect 635.

Figure 1: Field (2013) Large Effect Required Sample Size

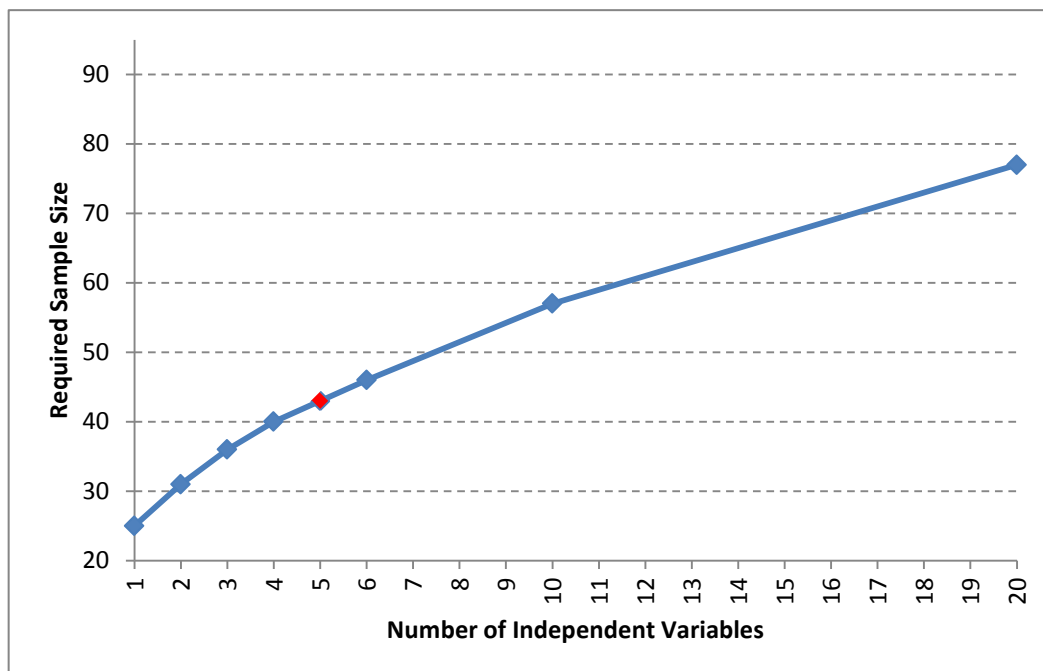


Figure 2: Field (2013) Medium Effect Required Sample Size

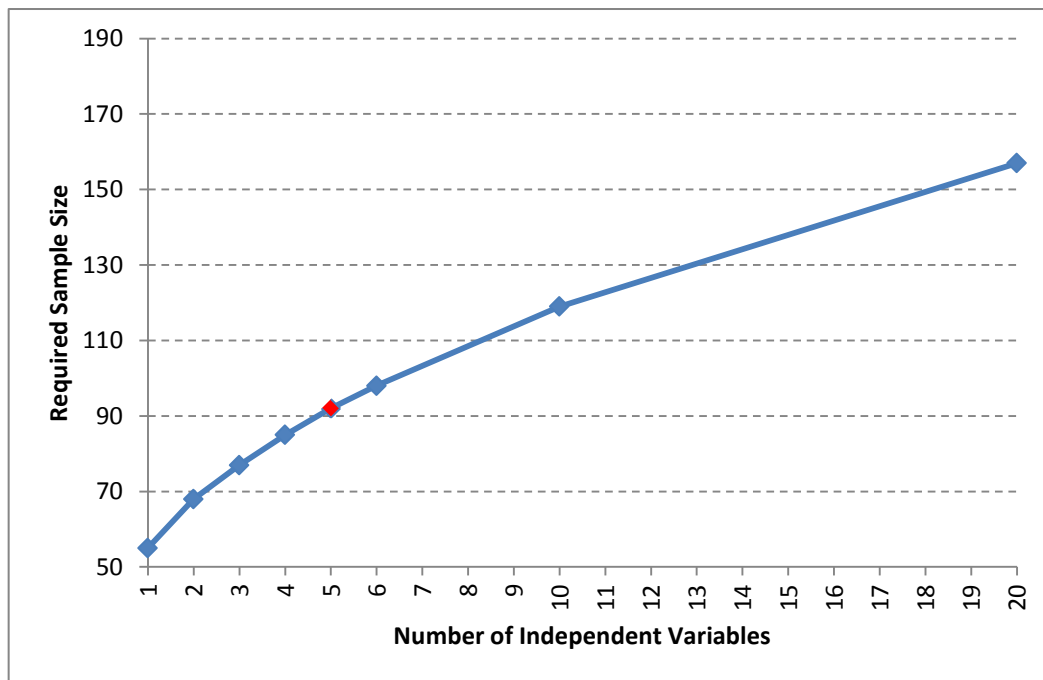
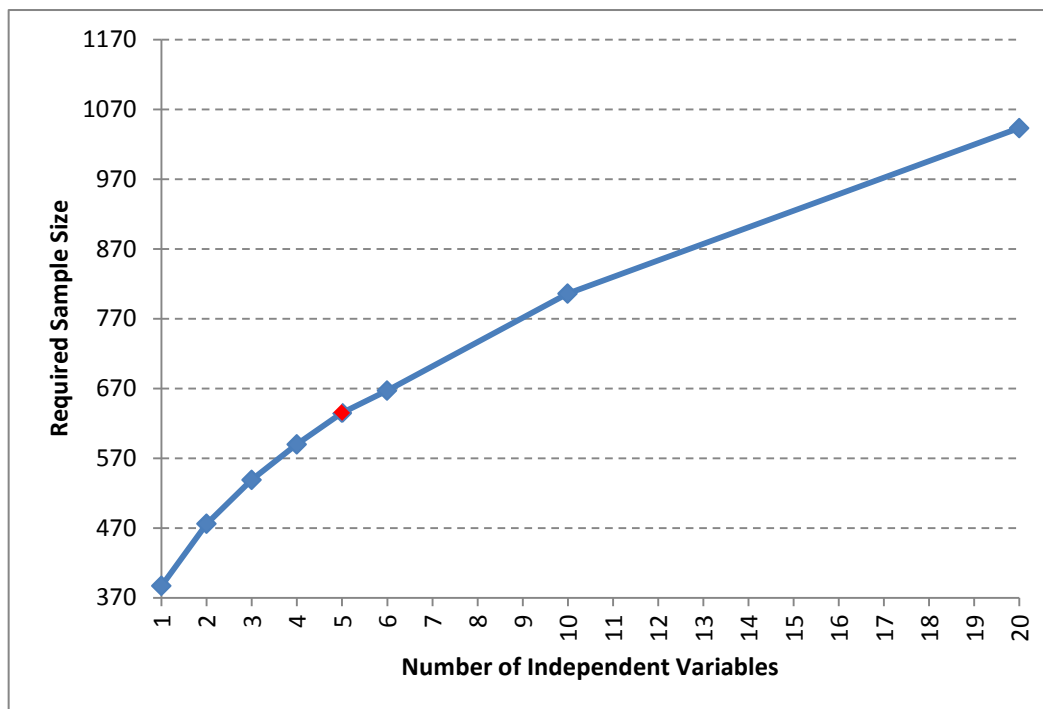


Figure 3: Field (2013) Small Effect Required Sample Size



As only ending share returns were evaluated in relation to the time spent in each optimised returns score quintile, only 114 observations could be made for non-resources and 25 for resources. This resulted in there being a limitation on detecting small effects where R^2 was less than 0.02 for the non-

resource model, and a limitation on detecting any effects on the resource model (Field, 2013).

Post all of the analyses and calculations a model was constituted, for each of the resources and non-resources groups, with percentage time coefficients which could be multiplied by each of the various quintile calculated coefficients.

4.8 Limitations

From a statistical perspective, there were certain limitations imposed, such as the inability to remove multicollinearity, which in reality never became a limitation in this study. Far more limiting was the incapability to confidently detect any effects for the resource shares and the inability to detect small effects the non-resource shares due to the size of the sample. This size of the sample could well have been increased through the use of more frequent return sampling, rather than just testing the total share's existence against its ending return, although this would have exposed the model to more volatility. As more financial data gets collected in future the frequency could be increased, without introducing excessive volatility, and would present an area for future research. Alternatively, the research could be opened up to shares outside the top 160 or the research could even be replicated on a larger exchange.

Survivorship bias was largely eliminated through the inclusion of delisted shares in all of the calculated portfolios, apart from the shares used for the calculation of the minimum variance zero-beta portfolios in the Black's CAPM analysis. This survivorship bias would only have applied to those shares that ceased to exist during to the time period being tested, so would be extremely small, but bears mentioning nonetheless.

Another source of survivorship bias was the use of only existing shares to compute the multiple regression models, but this was justified as attempting to project future returns for shares that had been delisted was nonsensical.

There were also certain non-statistical limitations imposed by using the selected sample. Perhaps most obviously, given the South African focus of this research, conclusions about international financial markets and the

associated cost of equity capital should be cautiously drawn, as each international exchange has marginally different regulations which may impact results. The South African focus also greatly reduced the number of prior research papers available for study and comparison, as comparatively few studies had been performed on South African financial data. Any unlisted firms were also not accounted for, and non-profit organisations were also not represented.

Amongst the potential alternative independent variables, the only distinction between industries was between resource shares and non-resource shares. However, this did not exclude the possibility that within specific industries, the independent variables may have had entirely different impacts on the dependent variable.

There were also numerous other potential independent variables, 316 of which were identified by Harvey et al. (2014), that may have been investigated but were excluded from this research in the interests of scale, and limited prior research recommending them as likely predictors of returns.

It should also be noted that the results may well not hold for equity traded prior to the date range under examination, nor into the future. In future, there may be external occurrences, such as legislative changes which may alter the relationships with the cost of equity. Although the use of market relative returns on equity in this study should have minimised this risk, certain external events may affect the cost of equity capital in such a way that other forms of financing may become preferable to the equity market as a whole.

The omission of transaction costs, while applied to all portfolios that were compared to reduce the impact, may have impacted certain portfolios more than others depending on the number of shares that were virtually traded into or out of a portfolio which may have skewed some of the results (Mutooni & Muller, 2007). Furthermore, transaction costs would, oftentimes, not have been a percentage of the total trade value, and could have been an absolute amount. Thus, larger value portfolios would have had relatively lower proportional transaction costs, whilst the issuance, or trading, of smaller values of equity may have been relatively more expensive due to the higher proportion of transaction costs that would have raised the required returns on equity to offset this.

The difference between bid and ask prices were also not taken into account, although the impact of this limitation would be expected to be marginal due to the highly liquid equity that was used in this research, as seen in the similar standard and Dimson' beta results.

The share prices used were only the end of trade prices so intraday fluctuations were ignored, which may have resulted in the research missing potential effects (Kappou, Brooks, & Ward, 2008). Additionally, only rebalancing portfolios at the start of each quarter may have meant that potential style effects were underestimated due to a slowness to respond based on the timing of rebalancing selected for this research.

The research also did not delve into the underlying reasons that the independent variables exhibited the correlations with the returns. Thus, the research only indicated whether a relationship existed and what the size of that relationship was, not the cause.

Furthermore, the research addressed and identified historical relationships, but as with any potential arbitrage opportunities the market would typically have responded to nullify those inefficiencies, particularly in the highly computerised era (Chaboud, Chiquoine, Hjalmarsson & Vega, 2014).

Finally, and potentially most pertinently, given the South African government's focus on developing small to medium sized enterprises (South African Presidency, 2011), these small to medium sized enterprises were excluded from the analysis as they had insufficient market capitalisation to be included in the top 160 shares.

Chapter 5 Results

5.1 Description of the Sample

The population was constituted of all shares with sufficient market capitalisation to be listed on the JSE's ALSI, and at the time of the research being conducted there were 171 such firms listed on the ALSI (Johannesburg Stock Exchange, 2015). The sample for this research was the top 160 shares, based on market capitalisation over the period 1985 until 2014, irrespective of whether they existed at the start of the period under review, nor whether they continued to exist throughout the period. The 160 firms sampled at any given time ensured it was possible to create equally weighted quintiles where required in the research.

5.2 Validity and Reliability of the Data

Validity refers to whether the instrument used to measure a phenomenon does indeed measure that phenomenon (Field, 2013). Upon first perusal this may appear to be a genuine concern around the measurements for this research as it claimed to be studying the cost of equity capital, yet the results obtained were all expressed in terms of share returns. However, cost of equity and share returns are actually equivalent, as any returns achieved by an external stakeholder could have been experienced by the original owners had they not sold that ownership stake. In this sense, any returns reflect the cost of having ceded that portion of the ownership. Hence, the research instrument was deemed valid.

Reliability, which has validity as a prerequisite, attempts to capture whether the results are repeatable in nature given the same conditions (Field, 2013). As financial markets are exposed to macroeconomic fluctuations, the exact environmental conditions would not be replicated throughout time. However, to attempt to minimise these fluctuations, where share returns were compared against each other over time, the percentage change in share price relative to the market was analysed. Through the use of market-relative measurements, macroeconomic occurrences were largely rendered immaterial as systemic

fluctuations were removed. This resulted in greatly increased reliability in the outcomes of this research.

5.3 Data Transformations Conducted

As per the methodology employed by Ward and Muller (2012), any changes in the share price that was the result of a share split or consolidation was backwards adjusted to the start of that quarter. Furthermore, where a subsidiary was spun-off, the returns of that subsidiary were combined with that of the original company for the remainder of that quarter, where after, each company was evaluated separately.

Again, as per the methodology of Ward and Muller (2012), cash dividends and scrip dividends were included in the returns on the shares, as they potentially constituted a large portion of the returns on equity capital. However, share buy backs and shares issued to managers were not included as they only held a potential impact for those shareholders who left the company (Ward & Muller, 2012).

Newly listed shares were only included from the start of the succeeding quarter. Delisted shares were excluded from the analysis from the following quarter, however, their returns were held at 0% from the date of their delisting as done by Ward and Muller (2012).

Where firms changed their names these were tracked and retrospectively changed to ensure consistency of the data for the entity despite the name change.

To remove any erroneous outliers in the data, any daily share return fluctuations greater than $\pm 40\%$ were excluded from the data, through making them 0% for that day.

5.4 Statistical Results

The statistical analysis tested each of the broad areas of this research in more detail. In so doing, the original CAPM, Black's CAPM and alternative pricing models were quantitatively tested.

The statistical testing was conducted in the same order as specified by the hypotheses and as laid out in the methodology section. However, there were certain common elements amongst the statistical analyses performed; primarily that statistical significance would only be regarded as proven at the 95% probability level, with two-tailed tests being used for all hypotheses.

5.4.1 Analysis of the Original CAPM

The primary difference between each of the tests conducted concerning the applicability of the original CAPM related to the beta look-back period employed, and the specific calculation of that beta. As such, the tests employed all followed a similar pattern by firstly graphically plotting the results for each time period against a 45 degree line, as a perfect correlation of 1 would have seen the CAPM predicted results and the actual returns fall onto that line. These graphical analyses are seen in Appendix 2 through 5.

Thereafter, descriptive and inferential statistics were computed. The descriptive statistics can be seen in Tables 1, 4, 7 and 10.

The inferential statistical analysis was performed through the application of a paired samples t-test. Firstly, to test if differences existed during the individual time series, and then to test if differences existed over the whole time period. These tests used a two-tailed test, with a 95% confidence level, as it was only used to ascertain if a significant difference existed between the various CAPM predictions and the actual share returns that were observed. These can be seen in Tables 2, 5, 8 and 11 for the time series statistics and 3, 6, 9 and 12 for the whole period statistics.

5.4.1.1 Tests of Hypothesis $H1a_0$

The following tables all reflect the results obtained utilising a 24 month look-back beta in the calculations. This resulted in 14 time periods that were tested.

Table 1: Descriptive Statistics for Original CAPM using 24 month beta

Date Range	Number of Firms	Number of Firms Removed	Look-back Period	Beta Type	Risk Free Rate Type	Risk Free Rate	Actual Correlation	Expected Correlation
31 Dec 1986 - 31 Dec 1988	160	0	24 months	Conventional	Government Bond Risk Free Proxy	14.2%	-4.28	1
31 Dec 1988 - 31 Dec 1990	160	0	24 months	Conventional	Government Bond Risk Free Proxy	14.7%	-4.32	1
31 Dec 1990 - 31 Dec 1992	160	0	24 months	Conventional	Government Bond Risk Free Proxy	14.8%	-5.04	1
31 Dec 1992 - 31 Dec 1994	160	0	24 months	Conventional	Government Bond Risk Free Proxy	13.6%	1.95	1
31 Dec 1994 - 31 Dec 1996	160	0	24 months	Conventional	Government Bond Risk Free Proxy	15.0%	-2.69	1
31 Dec 1996 - 31 Dec 1998	160	0	24 months	Conventional	Government Bond Risk Free Proxy	14.6%	-0.42	1
31 Dec 1998 - 31 Dec 2000	160	0	24 months	Conventional	Government Bond Risk Free Proxy	14.5%	-1.46	1
31 Dec 2000 - 31 Dec 2002	160	0	24 months	Conventional	Government Bond Risk Free Proxy	12.3%	-1.79	1
31 Dec 2002 - 31 Dec 2004	160	0	24 months	Conventional	Government Bond Risk Free Proxy	11.2%	-2.91	1
31 Dec 2004 - 31 Dec 2006	160	0	24 months	Conventional	Government Bond Risk Free Proxy	9.8%	0.38	1

31 Dec 2006 - 31 Dec 2008	160	0	24 months	Conventional	Government Bond Risk Free Proxy	9.7%	0.23	1
31 Dec 2008 - 31 Dec 2010	160	0	24 months	Conventional	Government Bond Risk Free Proxy	9.0%	0.35	1
31 Dec 2010 - 31 Dec 2012	160	0	24 months	Conventional	Government Bond Risk Free Proxy	8.6%	0.15	1
31 Dec 2012 - 31 Dec 2014	160	0	24 months	Conventional	Government Bond Risk Free Proxy	8.0%	-0.82	1

The descriptive statistics shown in Table 1 indicated what appeared to be noteworthy differences between the observed correlation between the actual results and those predicted by the original CAPM utilising a conventional 24 month look-back beta. The correlations in nine out of the 14 time periods observed were found to be negative.

These differences were also highly evident when depicted graphically in Appendix 2, where each of the time periods was graphed to show the correlation between the CAPM predicted returns and the actual returns. Each graph showed a red 45 degree line which would indicate perfect positive correlation i.e. correlation is 1. If the returns were correlated the black trend lines would be expected to lie on, or near, to the red perfect correlation line, which they appear not to do in any of Figure 14 through Figure 27. Furthermore, the predicted CAPM values appeared to have a far smaller range than the actual returns.

The inferential statistics for the 24 month look-back beta CAPM predicted results versus the actual results are shown in the tables below.

Table 2: Inferential Time Series Statistics for Original CAPM using 24 month beta

Date Range	Number of Firms	Paired Differences					t Score	Degrees of Freedom	Significance (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval				
					Lower	Upper			
31 Dec 1986 - 31 Dec 1988	160	0.065	0.333	0.026	0.013	0.117	2.461	159	0.015*
31 Dec 1988 - 31 Dec 1990	160	0.019	0.280	0.022	-0.024	0.063	0.880	159	0.380
31 Dec 1990 - 31 Dec 1992	160	0.131	0.394	0.031	0.070	0.193	4.224	159	0.000*
31 Dec 1992 - 31 Dec 1994	160	-0.262	0.429	0.034	-0.329	-0.194	-7.704	159	0.000*
31 Dec 1994 - 31 Dec 1996	160	0.133	0.245	0.019	0.095	0.171	6.863	159	0.000*
31 Dec 1996 - 31 Dec 1998	160	0.270	0.321	0.025	0.220	0.320	10.629	159	0.000*
31 Dec 1998 - 31 Dec 2000	160	-0.068	0.419	0.033	-0.133	-0.002	-2.043	159	0.043*
31 Dec 2000 - 31 Dec 2002	160	0.074	0.440	0.035	0.005	0.142	2.116	159	0.036*
31 Dec 2002 - 31 Dec 2004	160	-0.152	0.447	0.035	-0.222	-0.082	-4.296	159	0.000*
31 Dec 2004 - 31 Dec 2006	160	-0.236	0.331	0.026	-0.288	-0.184	-9.006	159	0.000*
31 Dec 2006 - 31 Dec 2008	160	0.224	0.206	0.016	0.191	0.256	13.721	159	0.000*
31 Dec 2008 - 31 Dec 2010	160	-0.138	0.249	0.020	-0.176	-0.099	-6.992	159	0.000*
31 Dec 2010 - 31 Dec 2012	160	0.063	0.287	0.023	0.018	0.107	2.763	159	0.006*
31 Dec 2012 - 31 Dec 2014	160	-0.002	0.293	0.023	-0.048	0.043	-0.105	159	0.916

* indicates significance at a 95% level.

Out of the 14 time periods analysed, 12 of them showed significant differences from the CAPM predicted results at a 95% confidence level. However, the two periods in which the CAPM with a 24 month look-back period could not be rejected appeared to show a strong probability that the CAPM predicted results and the actual results were drawn from the same population.

$H1a_0$ investigated the applicability of the CAPM with a 24 month look-back beta for the entire time period, and not merely the time series within. The results of this analysis are reflected in Table 3.

Table 3: Inferential Whole Period Statistics for Original CAPM using 24 month beta

Date Range	Number of Comparisons	Paired Differences					t Score	Degrees of Freedom	Significance (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval				
					Lower	Upper			
31 Dec 1986 - 31 Dec 2014	2240	0.009	0.376	0.008	-0.007	0.024	1.088	2239	0.276

* indicates significance at a 95% level.

5.4.1.2 Tests of Hypothesis $H1b_0$

The tests below all reflected the results obtained utilising a 60 month look-back beta in the calculations. This generated 5 time series for time series analysis.

Table 4: Descriptive Statistics for Original CAPM using 60 month beta

Date Range	Number of Firms	Number of Firms Removed	Look-back Period	Beta Type	Risk Free Rate Type	Risk Free Rate	Actual Correlation	Expected Correlation
31 Dec 1989 - 31 Dec 1994	160	0	60 months	Conventional	Government Bond Risk Free Proxy	14.6%	-3.74	1
31 Dec 1994 - 31 Dec 1999	160	0	60 months	Conventional	Government Bond Risk Free Proxy	15.0%	-0.47	1
31 Dec 1999 - 31 Dec 2004	160	0	60 months	Conventional	Government Bond Risk Free Proxy	12.9%	-1.74	1
31 Dec 2004 - 31 Dec 2009	160	0	60 months	Conventional	Government Bond Risk Free Proxy	9.8%	-0.32	1
31 Dec 2009 - 31 Dec 2014	160	0	60 months	Conventional	Government Bond Risk Free Proxy	9.3%	-2.11	1

The descriptive statistics shown in Table 4 indicated what appeared to be noteworthy differences between the observed correlation between the actual results and those predicted by the original CAPM utilising a conventional 60 month look-back beta. The correlations in all 5 of the time periods observed were found to be negative.

These differences were also highly evident when depicted graphically in Appendix 3, where each of the time periods was graphed to show the correlation between the CAPM predicted returns and the actual returns. Here too, each graph showed the 45 degree perfect correlation line in red. Yet again, the predicted CAPM values appeared to have a far smaller range than the actual returns.

The inferential statistics for the 60 month look-back beta CAPM predicted results versus the actual results are shown in the tables below.

Table 5: Inferential Time Series Statistics for Original CAPM using 60 month beta

Date Range	Number of Firms	Paired Differences					t Score	Degrees of Freedom	Significance (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval				
					Lower	Upper			
31 Dec 1989 - 31 Dec 1994	160	0.052	0.232	0.018	0.015	0.088	2.814	159	0.006*
31 Dec 1994 - 31 Dec 1999	160	0.145	0.190	0.015	0.115	0.174	9.648	159	0.000*
31 Dec 1999 - 31 Dec 2004	160	0.103	0.236	0.019	0.066	0.140	5.525	159	0.000*
31 Dec 2004 - 31 Dec 2009	160	0.009	0.186	0.015	-0.020	0.038	0.582	159	0.561
31 Dec 2009 - 31 Dec 2014	160	0.062	0.250	0.020	0.023	0.101	3.144	159	0.002*

* indicates significance at a 95% level.

In all of the time periods tested, bar one (31 Dec 2004 - 31 Dec 2009), a significant difference between the CAPM predicted results and the actual results was found, however, hypothesis $H1b_0$ referred to the entire time period as seen in Table 6 below.

Table 6: Inferential Whole Period Statistics for Original CAPM using 60 month beta

Date Range	Number of Comparisons	Paired Differences					t Score	Degrees of Freedom	Significance (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval				
					Lower	Upper			
31 Dec 1989 - 31 Dec 2014	800	0.074	0.224	0.008	0.058	0.090	9.323	799	0.000*

* indicates significance at a 95% level.

5.4.1.3 Tests of Hypothesis $H1c_0$

The following tests were identical to those performed for hypothesis $H1a_0$, however, the beta used was a 24 month look-back period Dimson' beta, with four lag periods and one leading period. This also resulted in 14 time periods that were tested.

Table 7: Descriptive Statistics for Original CAPM using Dimson 24 month beta

Date Range	Number of Firms	Number of Firms Removed	Look-back Period	Beta Type	Risk Free Rate Type	Risk Free Rate	Actual Correlation	Expected Correlation
31 Dec 1986 - 31 Dec 1988	160	0	24 months	Dimson	Government Bond Risk Free Proxy	14.2%	-0.40	1
31 Dec 1988 - 31 Dec 1990	160	0	24 months	Dimson	Government Bond Risk Free Proxy	14.7%	-3.33	1
31 Dec 1990 - 31 Dec 1992	160	0	24 months	Dimson	Government Bond Risk Free Proxy	14.8%	-2.28	1
31 Dec 1992 - 31 Dec 1994	160	0	24 months	Dimson	Government Bond Risk Free Proxy	13.6%	2.14	1
31 Dec 1994 - 31 Dec 1996	160	0	24 months	Dimson	Government Bond Risk Free Proxy	15.0%	-0.63	1
31 Dec 1996 - 31 Dec 1998	160	0	24 months	Dimson	Government Bond Risk Free Proxy	14.6%	-0.50	1
31 Dec 1998 - 31 Dec 2000	160	0	24 months	Dimson	Government Bond Risk Free Proxy	14.5%	-0.74	1

31 Dec 2000 - 31 Dec 2002	160	0	24 months	Dimson	Government Bond Risk Free Proxy	12.3%	-0.86	1
31 Dec 2002 - 31 Dec 2004	160	0	24 months	Dimson	Government Bond Risk Free Proxy	11.2%	-1.87	1
31 Dec 2004 - 31 Dec 2006	160	0	24 months	Dimson	Government Bond Risk Free Proxy	9.8%	-0.26	1
31 Dec 2006 - 31 Dec 2008	160	0	24 months	Dimson	Government Bond Risk Free Proxy	9.7%	0.24	1
31 Dec 2008 - 31 Dec 2010	160	0	24 months	Dimson	Government Bond Risk Free Proxy	9.0%	-0.06	1
31 Dec 2010 - 31 Dec 2012	160	0	24 months	Dimson	Government Bond Risk Free Proxy	8.6%	-0.06	1
31 Dec 2012 - 31 Dec 2014	160	0	24 months	Dimson	Government Bond Risk Free Proxy	8.0%	0.00	1

The descriptive statistics shown in Table 7 indicated what appeared to be noteworthy differences between the observed correlation between the actual results and those predicted by the original CAPM utilising a 24 month look-back Dimson' beta. The correlations in 11 of the 14 time periods observed were found to be negative.

These differences were also highly evident when depicted graphically in Appendix 4, where each of the time periods was graphed to show the correlation between the CAPM predicted returns and the actual returns. Here too, each graph showed the 45 degree perfect correlation line in red. The Dimson' beta appeared to create a wider dispersion of expected CAPM results than that rendered by the conventional beta calculation as seen in Appendix 2.

The inferential statistics for the 24 month look-back Dimson' beta CAPM predicted results versus the actual results are shown in the tables below.

Table 8: Inferential Time Series Statistics for Original CAPM using Dimson 24 month beta

Date Range	Number of Firms	Paired Differences					t Score	Degrees of Freedom	Significance (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval				
					Lower	Upper			
31 Dec 1986 - 31 Dec 1988	160	0.079	0.333	0.026	0.027	0.131	2.985	159	0.003*
31 Dec 1988 - 31 Dec 1990	160	0.022	0.285	0.023	-0.022	0.067	0.992	159	0.323
31 Dec 1990 - 31 Dec 1992	160	0.131	0.404	0.032	0.068	0.194	4.100	159	0.000*
31 Dec 1992 - 31 Dec 1994	160	-0.261	0.420	0.033	-0.327	-0.196	-7.864	159	0.000*
31 Dec 1994 - 31 Dec 1996	160	0.125	0.277	0.022	0.082	0.168	5.721	159	0.000*
31 Dec 1996 - 31 Dec 1998	160	0.270	0.335	0.026	0.218	0.322	10.192	159	0.000*
31 Dec 1998 - 31 Dec 2000	160	-0.049	0.444	0.035	-0.119	0.020	-1.404	159	0.162
31 Dec 2000 - 31 Dec 2002	160	0.094	0.465	0.037	0.022	0.167	2.562	159	0.011*
31 Dec 2002 - 31 Dec 2004	160	-0.167	0.468	0.037	-0.240	-0.094	-4.507	159	0.000*
31 Dec 2004 - 31 Dec 2006	160	-0.214	0.353	0.028	-0.269	-0.158	-7.647	159	0.000*
31 Dec 2006 - 31 Dec 2008	160	0.265	0.219	0.017	0.231	0.299	15.343	159	0.000*
31 Dec 2008 - 31 Dec 2010	160	-0.129	0.265	0.021	-0.170	-0.088	-6.169	159	0.000*
31 Dec 2010 - 31 Dec 2012	160	0.074	0.294	0.023	0.028	0.120	3.183	159	0.002*

31 Dec 2012 - 31 Dec 2014	160	-0.001	0.300	0.024	-0.047	0.046	-0.022	159	0.983
* indicates significance at a 95% level.									

Out of the 14 time periods analysed, 11 of them showed significant differences from the CAPM predicted results at a 95% confidence level. However, the three periods in which the CAPM with a 24 month look-back period Dimson' beta could not be rejected appeared to show a strong likelihood that the CAPM predicted results and the actual results were drawn from the same population.

$H1c_0$ investigated the applicability of the CAPM with a 24 month look-back Dimson' beta for the entire time period, and not merely the individual time series within. The results of this analysis are reflected in Table 9.

Table 9: Inferential Whole Period Statistics for Original CAPM using Dimson 24 month beta

Date Range	Number of Comparisons	Paired Differences					t Score	Degrees of Freedom	Significance (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval				
					Lower	Upper			
31 Dec 1986 - 31 Dec 2014	2240	0.017	0.389	0.008	0.001	0.033	2.089	2239	0.037*
* indicates significance at a 95% level.									

5.4.1.4 Tests of Hypothesis $H1d_0$

The tests conducted for hypothesis $H1d_0$ were the same as for hypothesis $H1b_0$ apart from the replacement of the conventional beta with the Dimson' beta, utilising a 60 month look-back period, with four lag periods and one leading period. Yet again, 5 time periods were obtained for the analysis.

Table 10: Descriptive Statistics for Original CAPM using Dimson 60 month beta

Date Range	Number of Firms	Number of Firms Removed	Look-back Period	Beta Type	Risk Free Rate Type	Risk Free Rate	Actual Correlation	Expected Correlation
31 Dec 1989 - 31 Dec 1994	160	0	60 months	Dimson	Government Bond Risk Free Proxy	14.6%	-1.38	1
31 Dec 1994 - 31 Dec 1999	160	0	60 months	Dimson	Government Bond Risk Free Proxy	15.0%	-0.64	1
31 Dec 1999 - 31 Dec 2004	160	0	60 months	Dimson	Government Bond Risk Free Proxy	12.9%	-0.59	1
31 Dec 2004 - 31 Dec 2009	160	0	60 months	Dimson	Government Bond Risk Free Proxy	9.8%	-0.28	1
31 Dec 2009 - 31 Dec 2014	160	0	60 months	Dimson	Government Bond Risk Free Proxy	9.3%	-1.50	1

The descriptive statistics shown in Table 10 indicated what appeared to be noteworthy differences between the observed correlation between the actual results and those predicted by the original CAPM utilising a 60 month look-back Dimson' beta. The correlations in all five of the time periods observed were found to be negative.

These differences were also highly evident when depicted graphically in Appendix 5, where each of the time periods was graphed to show the correlation between the CAPM predicted returns and the actual returns. Here too, each graph showed the 45 degree perfect correlation line in red. Unlike with the 24 month look-back period Dimson' beta, the Dimson' beta utilising a 60 month look-back period did not result in a visibly more dispersed range of predicted results than the conventional beta equivalent as seen in Appendix 3.

The inferential statistics for the 60 month look-back Dimson' beta CAPM predicted results versus the actual results are shown in the tables below.

Table 11: Inferential Time Series Statistics for Original CAPM using Dimson 60 month beta

Date Range	Number of Firms	Paired Differences					t Score	Degrees of Freedom	Significance (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval				
					Lower	Upper			
31 Dec 1989 - 31 Dec 1994	160	0.048	0.229	0.018	0.013	0.084	2.674	159	0.008*
31 Dec 1994 - 31 Dec 1999	160	0.143	0.205	0.016	0.110	0.175	8.788	159	0.000*
31 Dec 1999 - 31 Dec 2004	160	0.112	0.242	0.019	0.074	0.150	5.843	159	0.000*
31 Dec 2004 - 31 Dec 2009	160	0.014	0.198	0.016	-0.017	0.044	0.872	159	0.385
31 Dec 2009 - 31 Dec 2014	160	0.077	0.262	0.021	0.036	0.118	3.716	159	0.000*

* indicates significance at a 95% level.

In four out of five the time periods tested a significant difference between the CAPM predicted results and the actual results was found, however, hypothesis $H1d_0$ referred to the entire time period as seen in Table 12 below.

Table 12: Inferential Whole Period Statistics for Original CAPM using Dimson 60 month beta

Date Range	Number of Comparisons	Paired Differences					t Score	Degrees of Freedom	Significance (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval				
					Lower	Upper			
31 Dec 1989 - 31 Dec 2014	800	0.079	0.232	0.008	0.063	0.094	9.578	799	0.000*

* indicates significance at a 95% level.

5.4.1.5 Summary of the Analysis of the Original CAPM

A summation of the significance of the difference between the predicted returns of each of the variants of the original CAPM and the actual results, over each time period is shown in Table 13.

Table 13: Summary of Inferential Time Series Statistics Outcomes for Original CAPM

Date Range	$H1a_0$	$H1b_0$	$H1c_0$	$H1d_0$
31 Dec 1986 - 31 Dec 1988	Sig.	--	Sig.	--
31 Dec 1988 - 31 Dec 1990	Non-Sig.	--	Non-Sig.	--
31 Dec 1990 - 31 Dec 1992	Sig.	--	Sig.	--
31 Dec 1992 - 31 Dec 1994	Sig.	--	Sig.	--
31 Dec 1994 - 31 Dec 1996	Sig.	--	Sig.	--
31 Dec 1996 - 31 Dec 1998	Sig.	--	Sig.	--
31 Dec 1998 - 31 Dec 2000	Sig.	--	Non-Sig.	--
31 Dec 2000 - 31 Dec 2002	Sig.	--	Sig.	--
31 Dec 2002 - 31 Dec 2004	Sig.	--	Sig.	--
31 Dec 2004 - 31 Dec 2006	Sig.	--	Sig.	--

31 Dec 2006 - 31 Dec 2008	Sig.	--	Sig.	--
31 Dec 2008 - 31 Dec 2010	Sig.	--	Sig.	--
31 Dec 2010 - 31 Dec 2012	Sig.	--	Sig.	--
31 Dec 2012 - 31 Dec 2014	Non-Sig.	--	Non-Sig.	--
31 Dec 1989 - 31 Dec 1994	--	Sig.	--	Sig.
31 Dec 1994 - 31 Dec 1999	--	Sig.	--	Sig.
31 Dec 1999 - 31 Dec 2004	--	Sig.	--	Sig.
31 Dec 2004 - 31 Dec 2009	--	Non-Sig.	--	Non-Sig.
31 Dec 2009 - 31 Dec 2014	--	Sig.	--	Sig.
Sig. = Significant at 95% level; Non-Sig = Not significant at 95% level; -- = Not tested over that time period				

In only seven out of the 38 observations was the applicability of the CAPM not significantly rejected at the 95% confidence level. Another point that was noted, is that in all but one of the time periods the test of the CAPM, whether using the conventional beta or the Dimson' beta, delivered the same statistical verdict.

The hypotheses were actually derived to test the whole time period under evaluation and a summary of these is presented in Table 14.

Table 14: Summary of Inferential Whole Period Statistics for Original CAPM

Date Range	$H1a_0$	$H1b_0$	$H1c_0$	$H1d_0$
31 Dec 1986 - 31 Dec 2014	Non-Sig.	--	Sig.	--

31 Dec 1989 - 31 Dec 2014	--	Sig.	--	Sig.
Sig. = Significant at 95% level; Non-Sig = Not significant at 95% level; -- = Not tested over that time period				

It can be seen that only for hypothesis $H1a_0$ was the null hypothesis not rejected at a 95% level, namely only the original CAPM with a 24 month look-back beta could have predicted the actual results.

5.4.2 Analysis of Black's CAPM

In the analysis of the Black's CAPM, both the beta calculation methods and look-back periods were altered, as with the original CAPM analysis. However, the risk free proxy rate was replaced by a calculated efficient minimum variance zero-beta portfolio rate of return.

In a similar method to that used for the test of the original CAPM, descriptive statistics were calculated, followed by a graphical representation to determine whether correlation was displayed between the predicted and actual results. Thereafter, inferential statistical analysis was again performed. Whilst the analysis was palpably the same, using two-tailed paired t-tests, the primary difference could be seen in the descriptive statistics which included statistics around the minimum variance zero-beta portfolio that was calculated. This gave insight into how representative the portfolio was and how it compared to the traditional risk free rate proxy.

5.4.2.1 Tests of Hypothesis $H2a_0$

The following tests all reflected the results obtained utilising a 24 month look-back beta in the calculations. This resulted in 14 time periods that were tested.

Table 15: Descriptive Statistics for Black's CAPM using 24 month beta

Date Range	Number of Firms	Number of Firms Removed	Look-back Period	Beta Type	Risk Free Rate Type	Firms used in Zero-Beta Portfolio Calc.	Risk Free Rate	Actual Correlation	Expected Correlation
31 Dec 1986 - 31 Dec 1988	160	0	24 months	Conventional	Black's Zero-Beta Portfolio Return	137	20.4%	-4.28	1
31 Dec 1988 - 31 Dec 1990	160	0	24 months	Conventional	Black's Zero-Beta Portfolio Return	138	15.1%	-4.32	1
31 Dec 1990 - 31 Dec 1992	160	0	24 months	Conventional	Black's Zero-Beta Portfolio Return	156	13.8%	-5.04	1
31 Dec 1992 - 31 Dec 1994	160	0	24 months	Conventional	Black's Zero-Beta Portfolio Return	151	32.1%	1.95	1
31 Dec 1994 - 31 Dec 1996	160	0	24 months	Conventional	Black's Zero-Beta Portfolio Return	155	21.3%	-2.69	1
31 Dec 1996 - 31 Dec 1998	160	0	24 months	Conventional	Black's Zero-Beta Portfolio Return	145	12.1%	-0.42	1
31 Dec 1998 - 31 Dec 2000	160	0	24 months	Conventional	Black's Zero-Beta Portfolio Return	137	-16.3%	-1.46	1
31 Dec 2000 - 31 Dec 2002	160	0	24 months	Conventional	Black's Zero-Beta Portfolio Return	140	3.0%	-1.79	1
31 Dec 2002 - 31 Dec 2004	160	0	24 months	Conventional	Black's Zero-Beta Portfolio Return	149	22.5%	-2.91	1

31 Dec 2004 - 31 Dec 2006	160	0	24 months	Conventional	Black's Zero- Beta Portfolio Return	152	28.0%	0.38	1
31 Dec 2006 - 31 Dec 2008	160	0	24 months	Conventional	Black's Zero- Beta Portfolio Return	148	25.5%	0.23	1
31 Dec 2008 - 31 Dec 2010	160	0	24 months	Conventional	Black's Zero- Beta Portfolio Return	144	-8.2%	0.35	1
31 Dec 2010 - 31 Dec 2012	160	0	24 months	Conventional	Black's Zero- Beta Portfolio Return	151	18.5%	0.15	1
31 Dec 2012 - 31 Dec 2014	160	0	24 months	Conventional	Black's Zero- Beta Portfolio Return	152	10.2%	-0.82	1

Table 15 showed the variables employed in the test of the Black's CAPM utilising a 24 month look-back beta. The first noteworthy point was the presence of potential survivorship bias in the calculation of the minimum variance zero-beta portfolio, seen by the fact that not all 160 shares were used to calculate the zero-beta portfolio. Furthermore, the zero-beta portfolio returned a risk free rate that was negative in two of the 14 time periods. Nine of the 14 time periods also found a negative correlation with the predicted Black's CAPM results.

The graphical analysis, seen in Appendix 6, also showed that the Black's CAPM predicted results fell in a far narrower range than the actual results observed. A noteworthy change from the original CAPM graphs, seen in Appendices 2 through 5, was the increased prevalence of the prediction of negative returns from the Black's CAPM and also the larger dispersion of predicted returns between time series, as a result of the more varied zero-beta portfolio returns when compared to the risk free rate proxies.

The inferential statistics for the 24 month look-back beta Black's CAPM predicted results versus the actual results are shown in the tables below.

Table 16: Inferential Time Series Statistics for Black's CAPM using 24 month beta

Date Range	Number of Firms	Paired Differences					t Score	Degrees of Freedom	Significance (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval				
					Lower	Upper			
31 Dec 1986 - 31 Dec 1988	160	0.126	0.333	0.026	0.074	0.178	4.801	159	0.000*
31 Dec 1988 - 31 Dec 1990	160	0.024	0.280	0.022	-0.020	0.067	1.071	159	0.286
31 Dec 1990 - 31 Dec 1992	160	0.122	0.394	0.031	0.061	0.183	3.919	159	0.000*
31 Dec 1992 - 31 Dec 1994	160	-0.077	0.429	0.034	-0.144	-0.010	-2.275	159	0.024*
31 Dec 1994 - 31 Dec 1996	160	0.195	0.245	0.019	0.157	0.234	10.109	159	0.000*
31 Dec 1996 - 31 Dec 1998	160	0.244	0.321	0.025	0.194	0.295	9.627	159	0.000*
31 Dec 1998 - 31 Dec 2000	160	-0.376	0.419	0.033	-0.441	-0.310	-11.337	159	0.000*
31 Dec 2000 - 31 Dec 2002	160	-0.020	0.440	0.035	-0.088	0.049	-0.564	159	0.573
31 Dec 2002 - 31 Dec 2004	160	-0.039	0.447	0.035	-0.109	0.031	-1.097	159	0.275
31 Dec 2004 - 31 Dec 2006	160	-0.053	0.331	0.026	-0.105	-0.001	-2.028	159	0.044*
31 Dec 2006 - 31 Dec 2008	160	0.382	0.206	0.016	0.350	0.414	23.419	159	0.000*
31 Dec 2008 - 31 Dec 2010	160	-0.309	0.249	0.020	-0.348	-0.270	-15.704	159	0.000*
31 Dec 2010 - 31 Dec 2012	160	0.162	0.287	0.023	0.117	0.207	7.158	159	0.000*

31 Dec 2012 - 31 Dec 2014	160	0.020	0.293	0.023	-0.026	0.066	0.872	159	0.385
* indicates significance at a 95% level.									

Out of the 14 time periods analysed, ten of them showed significant differences from the Black's CAPM predicted results at a 95% confidence level.

$H2a_0$ investigated the applicability of the Black's CAPM with a 24 month look-back beta for the entire time period, and not merely the individual time series within. The results of this analysis were reflected in Table 17.

Table 17: Inferential Whole Period Statistics for Black's CAPM using 24 month beta

Date Range	Number of Comparisons	Paired Differences				t Score	Degrees of Freedom	Significance (2-tailed)	
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval				
					Lower				Upper
31 Dec 1986 - 31 Dec 2014	2240	0.029	0.394	0.008	0.012	0.045	3.453	2239	0.001*
* indicates significance at a 95% level.									

5.4.2.2 Tests of Hypothesis $H2b_0$

The tests below all reflected the results obtained utilising a 60 month look-back beta in the calculations. This generated five time series for analysis.

Table 18: Descriptive Statistics for Black's CAPM using 60 month beta

Date Range	Number of Firms	Number of Firms Removed	Look-back Period	Beta Type	Risk Free Rate Type	Firms used in Zero-Beta Portfolio Calc.	Risk Free Rate	Actual Correlation	Expected Correlation
31 Dec 1989 - 31 Dec 1994	160	0	60 months	Conventional	Black's Zero-Beta Portfolio Return	118	13.2%	-3.74	1
31 Dec 1994 - 31 Dec 1999	160	0	60 months	Conventional	Black's Zero-Beta Portfolio Return	145	23.5%	-0.47	1
31 Dec 1999 - 31 Dec 2004	160	0	60 months	Conventional	Black's Zero-Beta Portfolio Return	112	6.3%	-1.74	1
31 Dec 2004 - 31 Dec 2009	160	0	60 months	Conventional	Black's Zero-Beta Portfolio Return	133	15.6%	-0.32	1
31 Dec 2009 - 31 Dec 2014	160	0	60 months	Conventional	Black's Zero-Beta Portfolio Return	128	8.1%	-2.11	1

Table 18 showed the variables employed in the test of the Black's CAPM utilising a 60 month look-back beta. The first noteworthy point is the increased presence of potential survivorship bias in the calculation of the minimum variance zero-beta portfolio, seen by the fact that fewer shares were generally utilised to calculate the minimum variance zero-beta portfolio than when a 24 month look-back period was used. However, the zero-beta portfolio returned no negative risk free rates, unlike with the 24 month look-back period. All five of the time periods returned a negative correlation with the predicted Black's CAPM results.

The graphical analysis, seen in Appendix 7, also shows that the Black's CAPM predicted results fell in a far narrower range than the actual results observed.

The inferential statistics for the 60 month look-back beta Black's CAPM predicted results versus the actual results are shown in the tables below.

Table 19: Inferential Time Series Statistics for Black's CAPM using 60 month beta

Date Range	Number of Firms	Paired Differences					t Score	Degrees of Freedom	Significance (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval				
					Lower	Upper			
31 Dec 1989 - 31 Dec 1994	160	0.038	0.232	0.018	0.002	0.074	2.071	159	0.040*
31 Dec 1994 - 31 Dec 1999	160	0.229	0.190	0.015	0.200	0.259	15.295	159	0.000*
31 Dec 1999 - 31 Dec 2004	160	0.038	0.236	0.019	0.001	0.074	2.008	159	0.046*
31 Dec 2004 - 31 Dec 2009	160	0.067	0.186	0.015	0.038	0.097	4.585	159	0.000*
31 Dec 2009 - 31 Dec 2014	160	0.050	0.250	0.020	0.011	0.089	2.532	159	0.012*

* indicates significance at a 95% level.

Out of the five time periods analysed, all of them showed significant differences from the Black's CAPM predicted results at a 95% confidence level.

However, $H2b_0$ investigated the applicability of the Black's CAPM with a 60 month look-back beta for the entire time period, and not merely the individual time series within. The results of this analysis were reflected in Table 20.

Table 20: Inferential Whole Period Statistics for Black's CAPM using 60 month beta

Date Range	Number of Comparisons	Paired Differences					t Score	Degrees of Freedom	Significance (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval				
					Lower	Upper			
31 Dec 1989 - 31 Dec 2014	800	0.046	0.229	0.008	0.030	0.062	5.696	799	0.000*

* indicates significance at a 95% level.

5.4.2.3 Tests of Hypothesis $H2c_0$

The following tests were identical to those performed for hypothesis $H2a_0$, however, the beta used was a 24 month look-back period Dimson' beta, with four lag periods and one leading period. This also resulted in 14 time periods that were tested.

Table 21: Descriptive Statistics for Black's CAPM using Dimson 24 month beta

Date Range	Number of Firms	Number of Firms Removed	Look-back Period	Beta Type	Risk Free Rate Type	Firms used in Zero-Beta Portfolio Calc.	Risk Free Rate	Actual Correlation	Expected Correlation
31 Dec 1986 - 31 Dec 1988	160	0	24 months	Dimson	Black's Zero-Beta Portfolio Return	137	20.4%	-0.40	1
31 Dec 1988 - 31 Dec 1990	160	0	24 months	Dimson	Black's Zero-Beta Portfolio Return	138	15.1%	-3.33	1

31 Dec 1990 - 31 Dec 1992	160	0	24 months	Dimson	Black's Zero- Beta Portfolio Return	156	13.8%	-2.28	1
31 Dec 1992 - 31 Dec 1994	160	0	24 months	Dimson	Black's Zero- Beta Portfolio Return	151	32.1%	2.14	1
31 Dec 1994 - 31 Dec 1996	160	0	24 months	Dimson	Black's Zero- Beta Portfolio Return	155	21.3%	-0.63	1
31 Dec 1996 - 31 Dec 1998	160	0	24 months	Dimson	Black's Zero- Beta Portfolio Return	145	12.1%	-0.50	1
31 Dec 1998 - 31 Dec 2000	160	0	24 months	Dimson	Black's Zero- Beta Portfolio Return	137	-16.3%	-0.74	1
31 Dec 2000 - 31 Dec 2002	160	0	24 months	Dimson	Black's Zero- Beta Portfolio Return	140	3.0%	-0.86	1
31 Dec 2002 - 31 Dec 2004	160	0	24 months	Dimson	Black's Zero- Beta Portfolio Return	149	22.5%	-1.87	1
31 Dec 2004 - 31 Dec 2006	160	0	24 months	Dimson	Black's Zero- Beta Portfolio Return	152	28.0%	-0.26	1
31 Dec 2006 - 31 Dec 2008	160	0	24 months	Dimson	Black's Zero- Beta Portfolio Return	148	25.5%	0.24	1
31 Dec 2008 - 31 Dec 2010	160	0	24 months	Dimson	Black's Zero- Beta Portfolio Return	144	-8.2%	-0.06	1
31 Dec 2010 - 31 Dec 2012	160	0	24 months	Dimson	Black's Zero- Beta Portfolio Return	151	18.5%	-0.06	1
31 Dec 2012 - 31 Dec 2014	160	0	24 months	Dimson	Black's Zero- Beta Portfolio Return	152	10.2%	-0.00	1

Table 21 showed the variables employed in the test of the Black's CAPM utilising a 24 month look-back Dimson' beta. Again it should be noted that there was potential survivorship bias in the calculation of the minimum variance zero-beta portfolio. Furthermore, the zero-beta portfolio returned two negative risk free rates. Additionally, 12 out of the 14 time periods produced a negative correlation with the predicted Black's CAPM results.

The graphical analysis, seen in Appendix 8, also showed that the Black's CAPM predicted results were dispersed in far wider ranges when using the Dimson' beta than when the conventional beta was used.

The inferential statistics for the 24 month look-back Dimson' beta Black's CAPM predicted results versus the actual results are shown in the tables below.

Table 22: Inferential Time Series Statistics for Black's CAPM using Dimson 24 month beta

Date Range	Number of Firms	Paired Differences					t Score	Degrees of Freedom	Significance (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval				
					Lower	Upper			
31 Dec 1986 - 31 Dec 1988	160	0.140	0.333	0.026	0.088	0.192	5.324	159	0.000*
31 Dec 1988 - 31 Dec 1990	160	0.027	0.285	0.023	-0.018	0.071	1.179	159	0.240
31 Dec 1990 - 31 Dec 1992	160	0.121	0.404	0.032	0.058	0.185	3.803	159	0.000*
31 Dec 1992 - 31 Dec 1994	160	-0.077	0.420	0.033	-0.142	-0.011	-2.314	159	0.022*
31 Dec 1994 - 31 Dec 1996	160	0.188	0.277	0.022	0.145	0.231	8.591	159	0.000*
31 Dec 1996 - 31 Dec 1998	160	0.245	0.335	0.026	0.192	0.297	9.232	159	0.000*
31 Dec 1998 - 31 Dec 2000	160	-0.357	0.444	0.035	-0.427	-0.288	-10.173	159	0.000*

31 Dec 2000 - 31 Dec 2002	160	0.001	0.465	0.037	-0.072	0.074	0.027	159	0.978
31 Dec 2002 - 31 Dec 2004	160	-0.053	0.468	0.037	-0.126	0.020	-1.444	159	0.151
31 Dec 2004 - 31 Dec 2006	160	-0.031	0.353	0.028	-0.086	0.024	-1.104	159	0.271
31 Dec 2006 - 31 Dec 2008	160	0.423	0.219	0.017	0.389	0.457	24.488	159	0.000*
31 Dec 2008 - 31 Dec 2010	160	-0.301	0.265	0.021	-0.342	-0.259	-14.365	159	0.000*
31 Dec 2010 - 31 Dec 2012	160	0.174	0.294	0.023	0.128	0.220	7.465	159	0.000*
31 Dec 2012 - 31 Dec 2014	160	0.022	0.300	0.024	-0.025	0.069	0.933	159	0.352

* indicates significance at a 95% level.

Out of the 14 time periods analysed, nine of them showed significant differences from the Black's CAPM predicted results at a 95% confidence level. However, of the five time periods where a significant difference was not detected some of the results were sizeable.

$H2c_0$ investigated the applicability of the Black's CAPM with a 24 month look-back Dimson' beta for the entire time period, and not merely the individual time series within. The results of this analysis are reflected in Table 23.

Table 23: Inferential Whole Period Statistics for Black's CAPM using Dimson 24 month beta

Date Range	Number of Comparisons	Paired Differences				t Score	Degrees of Freedom	Significance (2-tailed)	
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval				
					Lower				Upper
31 Dec 1986 - 31 Dec 2014	2240	0.037	0.406	0.009	0.020	0.054	4.340	2239	0.000*

* indicates significance at a 95% level.

5.4.2.4 Tests of Hypothesis $H2d_0$

The tests conducted for hypothesis $H2d_0$ were the same as for hypothesis $H2b_0$ apart from the replacement of the conventional beta with the Dimson' beta, utilising a 60 month look-back period, with four lag periods and one leading period. Yet again, 5 time periods were obtained for the analysis.

Table 24: Descriptive Statistics for Black's CAPM using Dimson 60 month beta

Date Range	Number of Firms	Number of Firms Removed	Look-back Period	Beta Type	Risk Free Rate Type	Firms used in Zero-Beta Portfolio Calc.	Risk Free Rate	Actual Correlation	Expected Correlation
31 Dec 1989 - 31 Dec 1994	160	0	60 months	Dimson	Black's Zero-Beta Portfolio Return	118	13.2%	-1.38	1
31 Dec 1994 - 31 Dec 1999	160	0	60 months	Dimson	Black's Zero-Beta Portfolio Return	145	23.5%	-0.64	1
31 Dec 1999 - 31 Dec 2004	160	0	60 months	Dimson	Black's Zero-Beta Portfolio Return	112	6.3%	-0.59	1
31 Dec 2004 - 31 Dec 2009	160	0	60 months	Dimson	Black's Zero-Beta Portfolio Return	133	15.6%	-0.28	1
31 Dec 2009 - 31 Dec 2014	160	0	60 months	Dimson	Black's Zero-Beta Portfolio Return	128	8.1%	-1.50	1

Table 24 showed the variables used in the test of the Black's CAPM utilising a 60 month look-back Dimson' beta. The first noteworthy point is the increased presence of potential survivorship bias in the calculation of the minimum variance zero-beta portfolio, seen by

the fact that fewer shares were generally utilised to calculate the minimum variance zero-beta portfolio than when a 24 month look-back period was used. However, the zero-beta portfolio returned no negative risk free rates, unlike with the 24 month look-back period. All five of the time periods returned a negative correlation with the predicted Black's CAPM results.

The graphical analysis, seen in Appendix 9, also showed that the Black's CAPM predicted results fell in a far narrower range than the actual results observed, although the ranges appeared to be wider than those produced using the original CAPM with conventional betas.

The inferential statistics for the 60 month look-back Dimson' beta Black's CAPM predicted results versus the actual results are shown in the tables below.

Table 25: Inferential Time Series Statistics for Black's CAPM using Dimson 60 month beta

Date Range	Number of Firms	Paired Differences					t Score	Degrees of Freedom	Significance (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval				
					Lower	Upper			
31 Dec 1989 - 31 Dec 1994	160	0.035	0.229	0.018	-0.001	0.070	1.920	159	0.057
31 Dec 1994 - 31 Dec 1999	160	0.227	0.205	0.016	0.195	0.259	14.011	159	0.000*
31 Dec 1999 - 31 Dec 2004	160	0.046	0.242	0.019	0.008	0.083	2.410	159	0.017*
31 Dec 2004 - 31 Dec 2009	160	0.073	0.198	0.016	0.042	0.103	4.643	159	0.000*
31 Dec 2009 - 31 Dec 2014	160	0.065	0.262	0.021	0.024	0.106	3.134	159	0.002*

* indicates significance at a 95% level.

Out of the five time periods analysed, only one of them did not show a significant difference from the Black's CAPM predicted results at a 95% confidence level.

However, $H2d_0$ investigated the applicability of the Black's CAPM with a 60 month look-back Dimson' beta for the entire time period, and not merely the individual time series within. The results of this analysis are reflected in Table 26.

Table 26: Inferential Whole Period Statistics for Black's CAPM using Dimson 60 month beta

Date Range	Number of Comparisons	Paired Differences					t Score	Degrees of Freedom	Significance (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval				
					Lower	Upper			
31 Dec 1989 - 31 Dec 2014	800	0.089	0.239	0.008	0.073	0.106	10.568	799	0.000*

* indicates significance at a 95% level.

5.4.2.5 Summary of the Analysis of the Black's CAPM

A summation of the significance of the difference between the predicted returns of each of the variants of the Black's CAPM and the actual results, over each time period, is shown in Table 27.

Table 27: Summary of Inferential Time Series Statistics Outcomes for Black's CAPM

Date Range	$H2a_0$	$H2b_0$	$H2c_0$	$H2d_0$
31 Dec 1986 - 31 Dec 1988	Sig.	--	Sig.	--

31 Dec 1988 - 31 Dec 1990	Non-Sig.	--	Non-Sig.	--
31 Dec 1990 - 31 Dec 1992	Sig.	--	Sig.	--
31 Dec 1992 - 31 Dec 1994	Sig.	--	Sig.	--
31 Dec 1994 - 31 Dec 1996	Sig.	--	Sig.	--
31 Dec 1996 - 31 Dec 1998	Sig.	--	Sig.	--
31 Dec 1998 - 31 Dec 2000	Sig.	--	Sig.	--
31 Dec 2000 - 31 Dec 2002	Sig.	--	Sig.	--
31 Dec 2002 - 31 Dec 2004	Non-Sig.	--	Non-Sig.	--
31 Dec 2004 - 31 Dec 2006	Non-Sig.	--	Non-Sig.	--
31 Dec 2006 - 31 Dec 2008	Sig.	--	Non-Sig.	--
31 Dec 2008 - 31 Dec 2010	Sig.	--	Sig.	--
31 Dec 2010 - 31 Dec 2012	Sig.	--	Sig.	--
31 Dec 2012 - 31 Dec 2014	Non-Sig.	--	Non-Sig.	--
31 Dec 1989 - 31 Dec 1994	--	Sig.	--	Non-Sig.
31 Dec 1994 - 31 Dec 1999	--	Sig.	--	Sig.
31 Dec 1999 - 31 Dec 2004	--	Sig.	--	Sig.
31 Dec 2004 - 31 Dec 2009	--	Sig.	--	Sig.

31 Dec 2009 - 31 Dec 2014	--	Sig.	--	Sig.
Sig. = Significant at 95% level; Non-Sig = Not significant at 95% level; -- = Not tested over that time period				

In ten out of the 38 observations the applicability of the Black's CAPM was not significantly rejected at the 95% confidence level. Another point that was noted is that in all but two of the time periods, the test of the Black's CAPM, whether using the conventional beta or the Dimson' beta, delivered the same statistical verdict.

The hypotheses were actually derived to test the whole time period under evaluation and a summary of these is presented in Table 28.

Table 28: Summary of Inferential Whole Period Statistics for Black's CAPM

Date Range	$H2a_0$	$H2b_0$	$H2c_0$	$H2d_0$
31 Dec 1986 - 31 Dec 2014	Sig.	--	Sig.	--
31 Dec 1989 - 31 Dec 2014	--	Sig.	--	Sig.
Sig. = Significant at 95% level; Non-Sig = Not significant at 95% level; -- = Not tested over that time period				

It can be seen that all of the tests found the presence of significant differences between the Black's CAPM predicted returns and the actual observed returns.

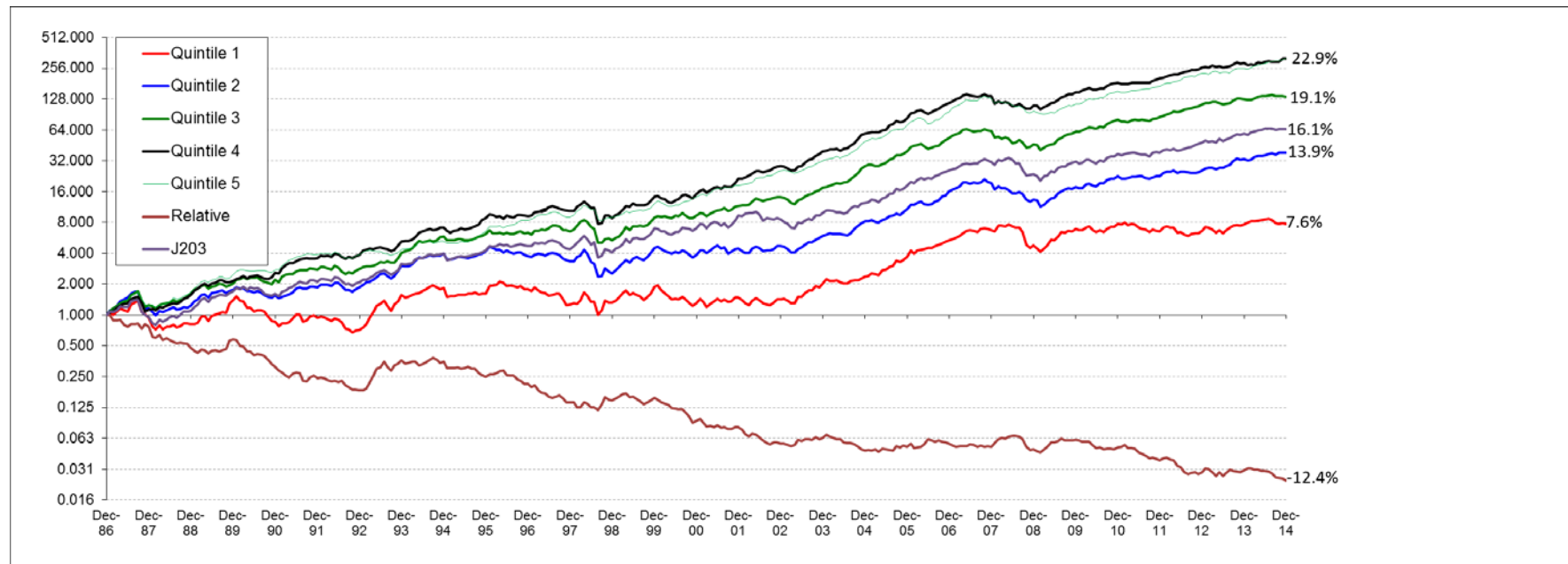
5.4.3 Consolidation of CAPM Findings

To consolidate the CAPM test findings the underlying tenet of the CAPM, which stated that higher betas would lead to higher returns, and vice versa, was tested.

5.4.3.1 Tests Performed for Consolidation

This was firstly done by ranking shares according to the 60 month conventional look-back betas, and forming virtual portfolios in the form of quintiles. Quintile 1 held the highest beta ranked scores and quintile 5 held the lowest beta ranked scores. The generated figure also included a price relative line to show the relationship across the time series, marked in brown on Figure 4 below.

Figure 4: Graphical Analysis of Beta Ranked Returns



The figure showed that the quintiles ranked from highest to lowest, according to effective annualised returns, were quintile 4, quintile 5, quintile 3, quintile 2 and finally quintile 1. The price relative, marked in brown also showed that for the majority of the time period the quintile with the lowest betas, quintile 5, consistently outperformed quintile 1, which contained the highest ranked betas.

Further descriptive statistics were shown in Table 29 to give a clearer indication of the apparent relationship.

Table 29: Descriptive Statistics for Beta Ranked Returns

Quintile	Number of Measures	Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval		Min.	Max
					Lower	Upper		
1	112	-0.016	0.087	0.008	-0.032	0.001	-0.225	0.226
2	112	-0.004	0.059	0.006	-0.015	0.007	-0.191	0.197
3	112	0.006	0.062	0.006	-0.005	0.018	-0.194	0.209
4	112	0.014	0.062	0.006	0.002	0.026	-0.173	0.202
5	112	0.013	0.071	0.007	-0.000	0.027	-0.252	0.171

Thereafter, as the first phase of the inferential statistics, the homogeneity of the variances was tested as this is a requirement for an ANOVA to be reliable. The outcome of this test is shown in Table 30.

Table 30: Beta Ranked Test for Homogeneity of Variances

Levene Statistic	df1	df2	Sig.
5.651	4	555	0.000*
* indicates significance at a 95% level.			

As can be seen, the Levene's test was significant, indicating probable heterogeneity of variances, thus, the ANOVA was replaced by the Welch test for this specific beta ranked returns analysis. The results of the Welch test are shown in Table 31 below.

Table 31: Beta Ranked Welch's Test

Welch Statistic	df1	df2	Sig.
3.145	4	276.461	0.015*
* indicates significance at a 95% level.			

The results of the Welch test showed that a statistically significant difference existed between the quintiles. The exact nature of the difference was seen through the use of the Tukey post hoc test as seen in Table 32 below.

Table 32: Beta Ranked Tukey Post Hoc Tests

Quintile	Comparison Quintiles	Mean Difference	Std. Error	Sig.	95% Confidence Interval	
					Lower	Upper
1	2	-0.012	0.009	0.702	-0.037	0.013
	3	-0.022	0.009	0.123	-0.047	0.003
	4	-0.030	0.009	0.012*	-0.055	-0.005
	5	-0.029	0.009	0.016*	-0.054	-0.004
2	1	0.012	0.009	0.702	-0.013	0.037
	3	-0.010	0.009	0.808	-0.035	0.015
	4	-0.018	0.009	0.297	-0.043	0.007
	5	-0.017	0.009	0.346	-0.042	0.008
3	1	0.022	0.009	0.123	-0.003	0.047
	2	0.010	0.009	0.808	-0.015	0.035
	4	-0.008	0.009	0.916	-0.033	0.017
	5	-0.007	0.009	0.943	-0.032	0.018
4	1	0.030	0.009	0.012*	0.005	0.055
	2	0.018	0.009	0.297	-0.007	0.043
	3	0.008	0.009	0.916	-0.017	0.033
	5	0.001	0.009	1.000	-0.024	0.026
5	1	0.029	0.009	0.016*	0.004	0.054
	2	0.017	0.009	0.346	-0.008	0.042
	3	0.007	0.009	0.943	-0.018	0.032
	4	-0.001	0.009	1.000	-0.026	0.024

5.4.4 Analysis of Alternative Pricing Models

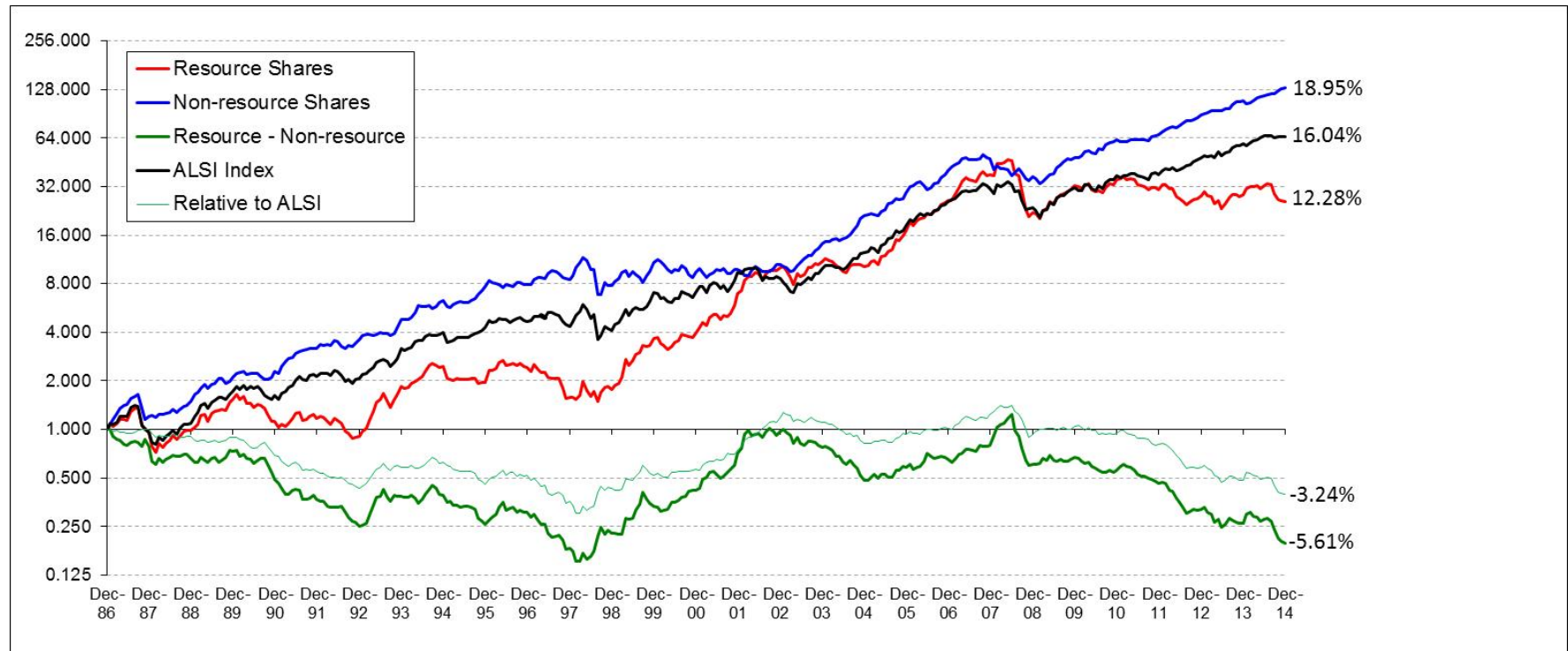
The general approach taken to test the styles was to test each style individually through observing returns graphically and then statistically examining them through the use of descriptive statistics and inferential statistics.

Thereafter, the combined effect of the styles was tested by calculating the return scores and showing the returns of the virtual portfolios formed based on these scores. The weighting of the underlying styles within these scores was then optimised, and the graphs were redrawn, given the optimised weighting. This was followed by utilising statistics to perform a multiple regression to attempt the generation of a general equation to be used to predict the expected future cost of equity for a given share, based on historical score rankings.

5.4.4.1 Analysis of the Sector Style

The first style to be tested was that of the sector, split according to whether a share was listed as being a resource or a non-resource share. Firstly, this was plotted as seen in Figure 5, commencing each trend line from 1, showing the experienced returns against a logarithmic scale. The trend lines included the returns on resource shares, non-resource shares and the ALSI. To allow for time series analysis two price relative lines were included showing the relative performance of the resource shares to the ALSI and the relative performance of the resource shares against the non-resource shares.

Figure 5: Graphical Analysis of Sector Returns



As can be seen in Figure 5 above, the non-resource shares showed higher returns of 18.95% than the resource shares, 12.28%. The ALSI relative depicted in Figure 5, light blue line, also showed that resource shares generally underperformed against the ALSI, except for two brief periods in 2002 and 2008. Furthermore, the price relative trend line of the difference between the resource shares' and non-resource shares' returns showed that non-resource shares outperformed the resource shares over almost the entire period.

The next analysis to be conducted was to calculate the descriptive statistics for the shares over the time period, as shown in Table 33.

Table 33: Descriptive Statistics for Resource vs Non-Resource Share Returns

	Number of Measures	Mean	Std. Deviation	Std. Error Mean
Non-Resources	112	0.006	0.069	0.007
Resources	112	-0.005	0.090	0.009

Thereafter, an independent t-test was conducted to determine if the non-resource shares statistically outperformed the resource shares over the entire period. The results of this analysis are shown in Table 34 below. Due to the significant failure, $p = 0.006$, of the test for homogeneity of variance (Levene's test), the figures shown for the t-test are those that apply in the case of homogeneity of variance not being present.

Table 34: Inferential Statistics for Resource vs Non-Resource Share Returns

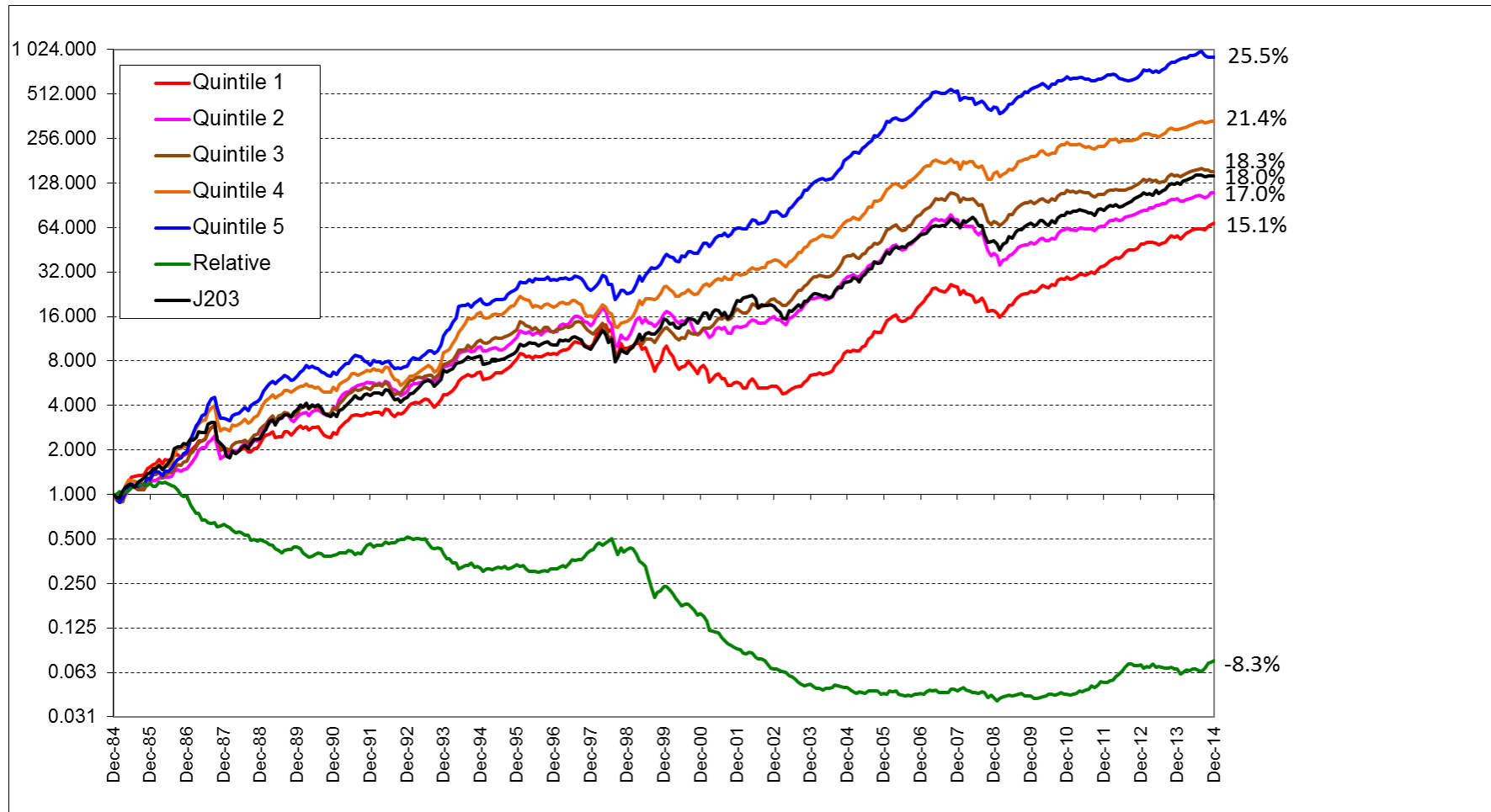
Date Range	Levene's test		t-test for Equality of Means							Cohen's <i>d</i>
	F	Sig.	t	Degrees of Freedom	Significance (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval		
								Lower	Upper	
31 Dec 1986 - 31 Dec 2014	7.823	0.006*	1.042	207.909	0.298	0.011	0.011	-0.010	0.032	0.122

5.4.4.2 Analysis of the Market-to-Book Style

The next style to be tested was that of the market-to-book style. Firstly, the shares were divided into five virtual portfolios based on their market-to-book ranking. These quintiles were plotted as seen in Figure 6, commencing each trend line from 1, showing the experienced returns against a logarithmic scale, with the quintiles being rebalanced each quarter to ensure that the correct ranking

according to market-to-book ratios remained in place. The trend lines included a price relative line to show the relative performance of the highest ranked quintile over the lowest ranked quintile over the time series. The trend line marked J203, in this graph and all those that follow, represented the returns of the JSE ALSI.

Figure 6: Graphical Analysis of Market-to-Book Returns



As can be seen, the quintiles with the lowest market-to-book ratios outperformed those with higher market-to-book ratios over the entire time period, with the performance in descending order being quintile 5, quintile 4, quintile 3, quintile 2, and quintile 1. However, it should be noted from the price relative line, in green, that since 2004 there had not been a significant out-performance, and higher market-to-book ratio equity even experienced a brief period of out-performance from 2011 to 2012.

Further descriptive statistics are shown in Table 35 to give a clearer indication of the apparent relationship.

Table 35: Descriptive Statistics for Market-to-Book Ranked Returns

Quintile	Number of Measures	Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval		Min.	Max
					Lower	Upper		
1	120	-0.005	0.081	0.007	-0.019	0.010	-0.299	0.260
2	120	-0.002	0.068	0.006	-0.014	0.010	-0.208	0.153
3	120	0.001	0.065	0.006	-0.011	0.012	-0.159	0.162
4	120	0.008	0.065	0.006	-0.004	0.019	-0.222	0.218
5	120	0.017	0.079	0.007	-0.002	0.031	-0.173	0.403

Thereafter, as the first phase of the inferential statistics, the homogeneity of the variances was tested as this is a requirement for an ANOVA to be reliable. The outcome of this test is shown in Table 36.

Table 36: Market-to-Book Ranked Test for Homogeneity of Variances

Levene Statistic	df1	df2	Sig.
0.741	4	595	0.564
* indicates significance at a 95% level.			

Given that the Levene test was not significant, the ANOVA was performed, as seen in Table 37 below.

Table 37: Market-to-Book Ranked ANOVA

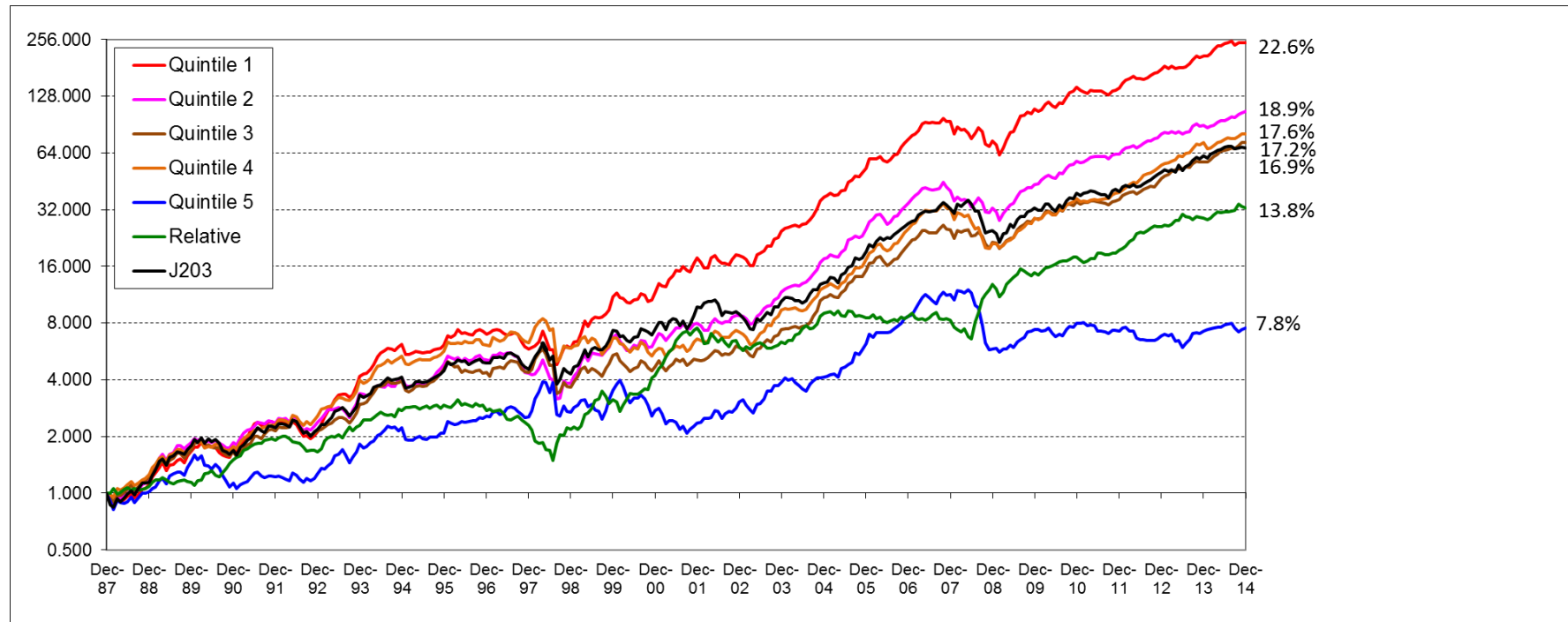
	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	0.035	4	0.009	1.700	0.148
Within Groups	3.076	595	0.005		
Total	3.111	599			
* indicates significance at a 95% level.					

The results of the ANOVA showed that no statistically significant differences existed between the quintiles. Thus, the Tukey post hoc tests were disregarded as there were no inter-quintile differences that needed identifying.

5.4.4.3 Analysis of the Earnings Yield Style

The following style to be analysed was that of the earnings yield style. Firstly, the shares were divided into five virtual portfolios based on their earnings yield ranking. These quintiles were plotted as seen in Figure 7, commencing each trend line from 1, showing the experienced returns against a logarithmic scale, with the quintiles being rebalanced each quarter to ensure that the correct ranking according to earnings yield ratios remained in place. The trend lines included a price relative line to show the relative performance of the highest ranked quintile over the lowest ranked quintile over the time series. It should also be highlighted that Figure 7 started from December 1987, due to not all of the firms' financial information being available from December 1984 until December 1987.

Figure 7: Graphical Analysis of Earnings Yield Returns



As can be seen, generally portfolios with higher earnings yields appeared to have outperformed those with lower earnings yields, with the portfolios' performance in descending order being quintile 1, quintile 2, quintile 4, quintile 3, and quintile 5. The price relative, in green, also indicated that the outperformance of higher earnings yield firms had been a relatively consistent phenomenon that still persisted.

Further descriptive statistics are shown in Table 38 to give a clearer indication of the apparent relationship.

Table 38: Descriptive Statistics for Earnings Yield Ranked Returns

Quintile	Number of Measures	Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval		Min.	Max
					Lower	Upper		
1	108	0.013	0.068	0.007	-0.000	0.026	-0.176	0.302
2	108	0.004	0.066	0.006	-0.009	0.017	-0.249	0.266
3	108	0.000	0.056	0.005	-0.010	0.011	-0.248	0.203
4	108	0.002	0.054	0.005	-0.009	0.012	-0.173	0.129
5	108	-0.019	0.068	0.007	-0.032	-0.006	-0.187	0.153

Thereafter, as the first phase of the inferential statistics, the homogeneity of the variances was tested as this is a requirement for an ANOVA to be reliable. The outcome of this test is shown in Table 39.

Table 39: Earnings Yield Ranked Test for Homogeneity of Variances

Levene Statistic	df1	df2	Sig.
1.406	4	535	0.231
* indicates significance at a 95% level.			

Given that the Levene test was not significant, the ANOVA was performed, as seen in Table 40 below.

Table 40: Earnings Yield Ranked ANOVA

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	0.061	4	0.015	3.832	0.004*
Within Groups	2.113	535	0.004		
Total	2.174	539			
* indicates significance at a 95% level.					

The results of the ANOVA test showed that a statistically significant difference existed between the quintiles. The exact nature of the difference was seen through the use of the Tukey post hoc test as seen in Table 41 below.

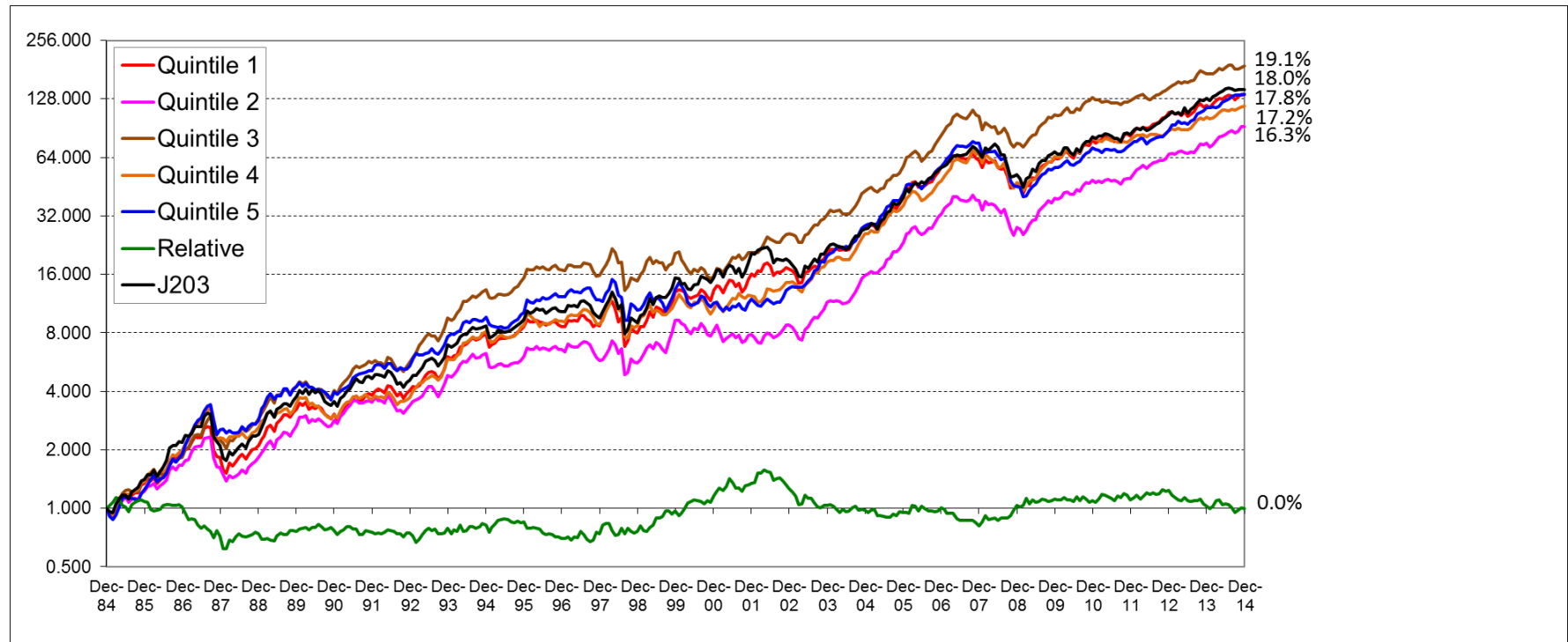
Table 41: Earnings Yield Ranked Tukey Post Hoc Tests

Quintile	Comparison Quintiles	Mean Difference	Std. Error	Sig.	95% Confidence Interval	
					Lower	Upper
1	2	0.009	0.009	0.852	-0.015	0.032
	3	0.013	0.009	0.583	-0.011	0.036
	4	0.011	0.009	0.681	-0.012	0.035
	5	0.032	0.009	0.002*	0.009	0.056
2	1	-0.009	0.009	0.852	-0.032	0.015
	3	0.004	0.009	0.991	-0.019	0.027
	4	0.003	0.009	0.998	-0.021	0.026
	5	0.024	0.009	0.047*	0.000	0.047
3	1	-0.013	0.009	0.583	-0.036	0.011
	2	-0.004	0.009	0.991	-0.027	0.019
	4	-0.001	0.009	1.000	-0.024	0.022
	5	0.020	0.009	0.148	-0.004	0.043
4	1	-0.011	0.009	0.681	-0.035	0.012
	2	-0.003	0.009	0.998	-0.026	0.021
	3	0.001	0.009	1.000	-0.022	0.025
	5	0.021	0.009	0.104	-0.002	0.044
5	1	-0.032	0.009	0.002	-0.056	-0.009
	2	-0.024	0.009	0.047	-0.047	-0.000
	3	-0.020	0.009	0.148	-0.043	0.004
	4	-0.021	0.009	0.104	-0.044	0.002

5.4.4.4 Analysis of the Company Size Style

The next style to be analysed was that of the company size style. Firstly, the shares were divided into five virtual portfolios based on their local market capitalisation ranking. These quintiles were plotted as seen in Figure 8, commencing each trend line from 1, showing the experienced returns against a logarithmic scale, with the quintiles being rebalanced each quarter to ensure that the correct ranking according to market capitalisation remained in place. The trend lines included a price relative line to show the comparative performance of the highest ranked quintile over the lowest ranked quintile over the complete time series.

Figure 8: Graphical Analysis of Company Size Returns



As evidenced by the graphic, there was minimal difference in returns between the different virtual portfolios. The returns in descending order were quintile 3, quintile 5, quintile 1, quintile 4, and quintile 2. The price relative, in green, also indicated that there was negligible difference in performance between the largest market capitalisation portfolio and the smallest.

Further descriptive statistics were shown in Table 42 to give a clearer indication of the apparent relationship.

Table 42: Descriptive Statistics for Company Size Ranked Returns

Quintile	Number of Measures	Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval		Min.	Max
					Lower	Upper		
1	120	-0.001	0.037	0.003	-0.007	0.006	-0.088	0.108
2	120	-0.004	0.058	0.005	-0.014	0.007	-0.215	0.198
3	120	0.002	0.065	0.006	-0.009	0.014	-0.228	0.205
4	120	-0.002	0.068	0.006	-0.014	0.011	-0.296	0.180
5	120	-0.000	0.071	0.006	-0.013	0.013	-0.193	0.191

Thereafter, as the first phase of the inferential statistics, the homogeneity of the variances was tested as this was a requirement for an ANOVA to be reliable. The outcome of this test is shown in Table 43.

Table 43: Company Size Ranked Test for Homogeneity of Variances

Levene Statistic	df1	df2	Sig.
7.989	4	595	0.000*
* indicates significance at a 95% level.			

As can be seen, the Levene's test was significant, indicating probable heterogeneity of variances, thus, the ANOVA was replaced by the Welch test for this specific company size ranked returns analysis. The results of the Welch test are shown in Table 44 below.

Table 44: Company Size Ranked Welch's Test

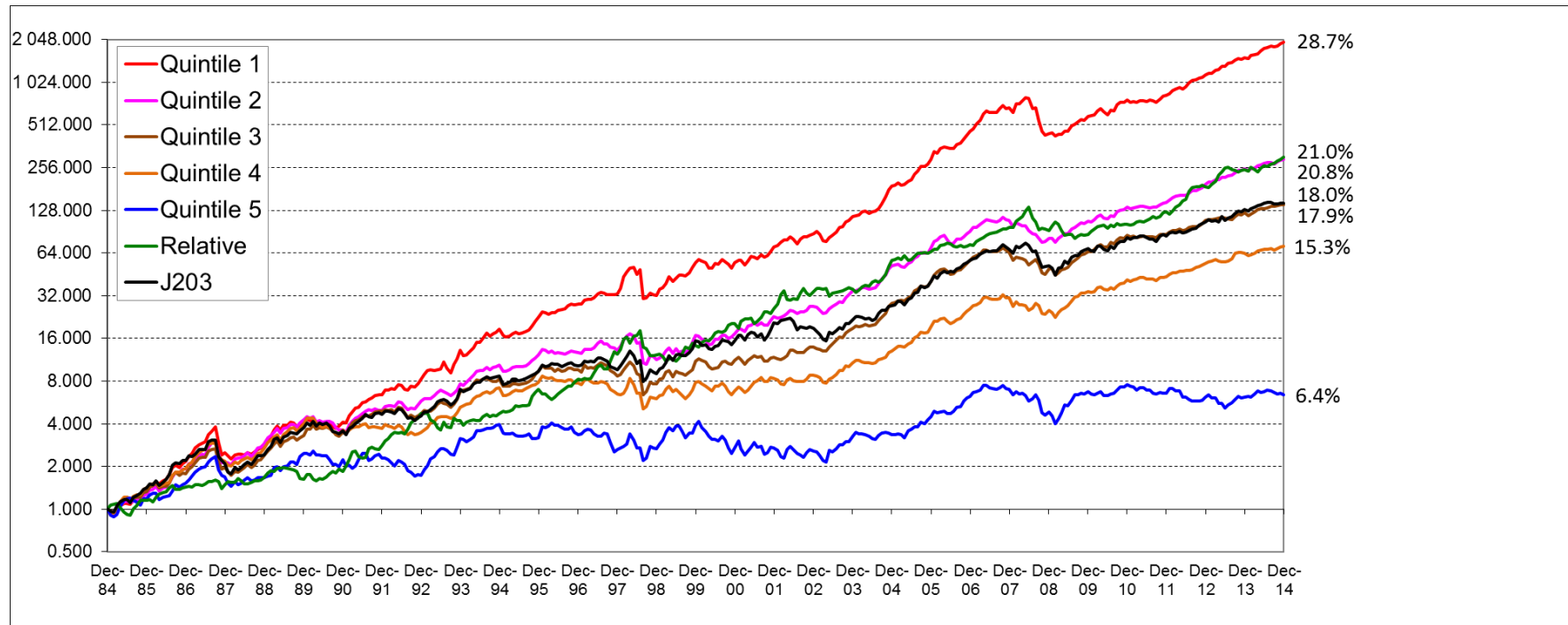
Welch Statistic	df1	df2	Sig.
0.144	4	290.791	0.965
* indicates significance at a 95% level.			

The results of the Welch test showed that no statistically significant differences existed between the quintiles. Thus, the Tukey post hoc tests were disregarded as there were no inter-quintile differences that needed identifying.

5.4.4.5 Analysis of the Momentum Style

The final style to be analysed was that of the momentum style, using 12 month historical momentum. Firstly, the shares were divided into five virtual portfolios based on their 12 month momentum ranking. These quintiles were plotted as seen in Figure 9, commencing each trend line from 1, showing the experienced returns against a logarithmic scale, with the quintiles being rebalanced each quarter to ensure that the correct ranking according to market capitalisation remained in place. The trend lines included a price relative line to show the relative performance of the highest ranked quintile over the lowest ranked quintile over the comprehensive time series.

Figure 9: Graphical Analysis of Momentum Returns



As can be seen, generally portfolios with higher momentum appeared to have outperformed those with lower momentum, with the portfolios' performance in descending order being quintile 1, quintile 2, quintile 3, quintile 4, and quintile 5. The price relative, in green, also indicated that the outperformance of higher momentum firms had been a relatively consistent phenomenon that still persisted.

Further descriptive statistics are shown in Table 45 to give a clearer indication of the apparent relationship.

Table 45: Descriptive Statistics for Momentum Ranked Returns

Quintile	Number of Measures	Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval		Min.	Max
					Lower	Upper		
1	120	0.025	0.062	0.006	0.013	0.036	-0.143	0.259
2	120	0.006	0.055	0.005	-0.004	0.016	-0.169	0.148
3	120	-0.000	0.060	0.005	-0.011	0.010	-0.246	0.213
4	120	-0.007	0.067	0.006	-0.019	0.005	-0.250	0.282
5	120	-0.024	0.083	0.008	-0.039	-0.009	-0.223	0.215

Thereafter, as the first phase of the inferential statistics, the homogeneity of the variances was tested as this was a requirement for an ANOVA to be reliable. The outcome of this test is shown in Table 46.

Table 46: Momentum Ranked Test for Homogeneity of Variances

Levene Statistic	df1	df2	Sig.
4.313	4	595	0.002*
* indicates significance at a 95% level.			

As can be seen, the Levene's test was significant, indicating probable heterogeneity of variances, thus, the ANOVA was replaced by the Welch test for this specific momentum ranked returns analysis. The results of the Welch test are shown in Table 47 below.

Table 47: Momentum Ranked Welch's Test

Welch Statistic	df1	df2	Sig.
7.661	4	296.399	0.000*
* indicates significance at a 95% level.			

The results of the Welch test showed that a statistically significant difference existed between the quintiles. The exact nature of the difference was seen through the use of the Tukey post hoc test as seen in Table 48 below.

Table 48: Momentum Ranked Tukey Post Hoc Tests

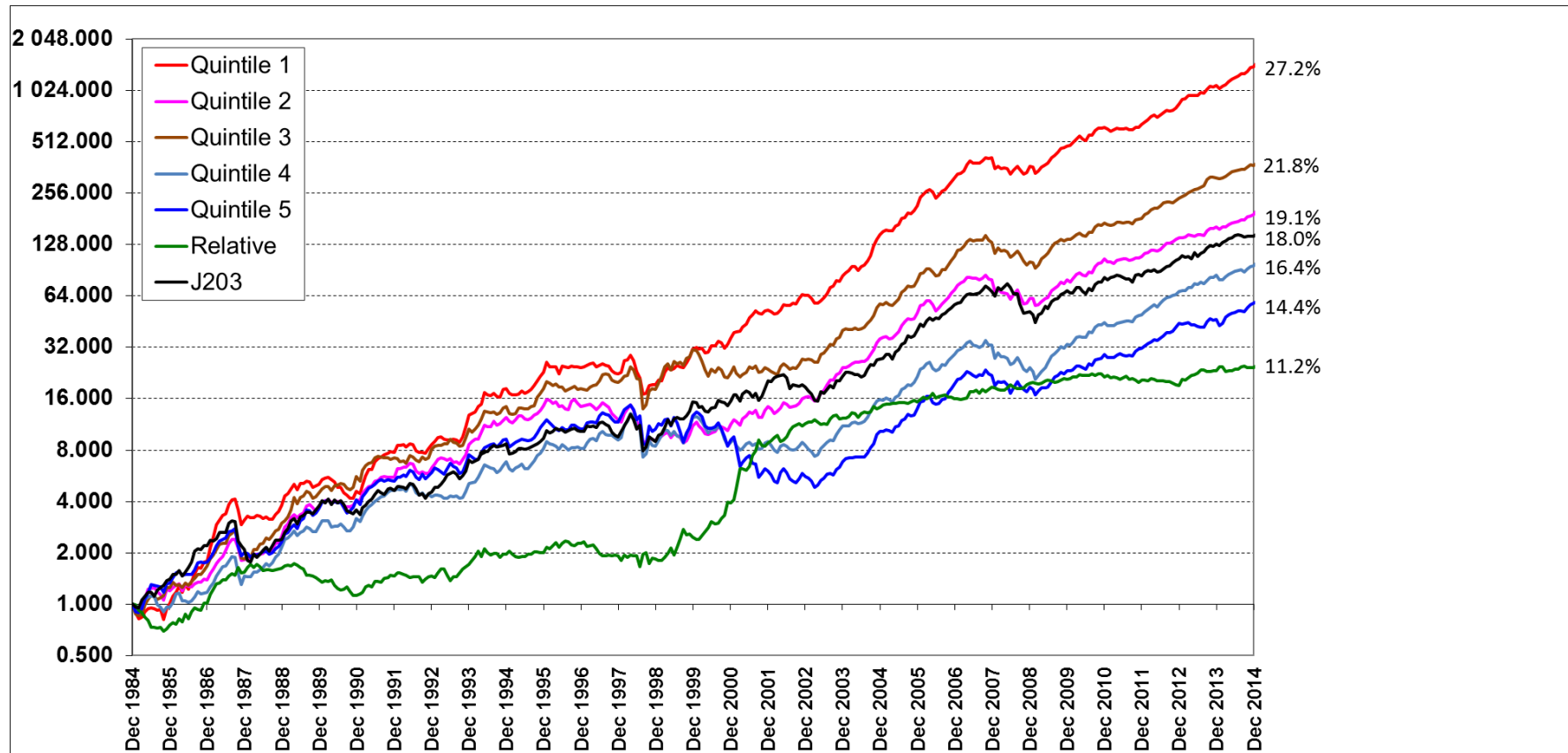
Quintile	Comparison Quintiles	Mean Difference	Std. Error	Sig.	95% Confidence Interval	
					Lower	Upper
1	2	0.019	0.009	0.186	-0.005	0.042
	3	0.025	0.009	0.029*	0.002	0.048
	4	0.031	0.009	0.002*	0.008	0.055
	5	0.049	0.009	0.000*	0.026	0.072
2	1	-0.019	0.009	0.186	-0.042	0.005
	3	0.006	0.009	0.947	-0.017	0.030
	4	0.013	0.009	0.562	-0.011	0.036
	5	0.030	0.009	0.004*	0.007	0.054
3	1	-0.025	0.009	0.029*	-0.048	-0.002
	2	-0.006	0.009	0.947	-0.030	0.017
	4	0.006	0.009	0.942	-0.017	0.030
	5	0.024	0.009	0.042*	0.001	0.047
4	1	-0.031	0.009	0.002*	-0.055	-0.008
	2	-0.013	0.009	0.562	-0.036	0.011
	3	-0.006	0.009	0.942	-0.030	0.017
	5	0.017	0.009	0.248	-0.006	0.041
5	1	-0.049	0.009	0.000*	-0.072	-0.026
	2	-0.030	0.009	0.004*	-0.054	-0.007
	3	-0.024	0.009	0.042*	-0.047	-0.001
	4	-0.017	0.009	0.248	-0.041	0.006

5.4.4.6 Analysis of the Combined Optimising Score Model

5.4.4.6.1 Non-Resource Analysis

Firstly, the non-resource shares were addressed, with equal weighting of the constituent styles, which, when mapped graphically, produced the returns per quintile as seen in Figure 10.

Figure 10: Unoptimised Returns Score Quintile Returns for Non-Resources



Even with no optimisation performed on the weightings of the constituent styles, the quintiles performed nearly as expected, apart from quintile 2 generating lower returns than quintile 3. This resulted in a descending order of quintile 1, quintile 3, quintile 2, quintile 4 and quintile 5. The price relative, however, shows what would be expected with quintile 1 consistently outperforming quintile 5.

Thereafter, optimisation was performed by holding momentum over the prior 12 months constant at 100%, due to the strong apparent relationship with returns observed in Figure 9 and Table 47, and optimising the weights of the remaining styles. This led to the weighting, as shown in Table 49.

Table 49: Optimisation Outputs for Non-Resources

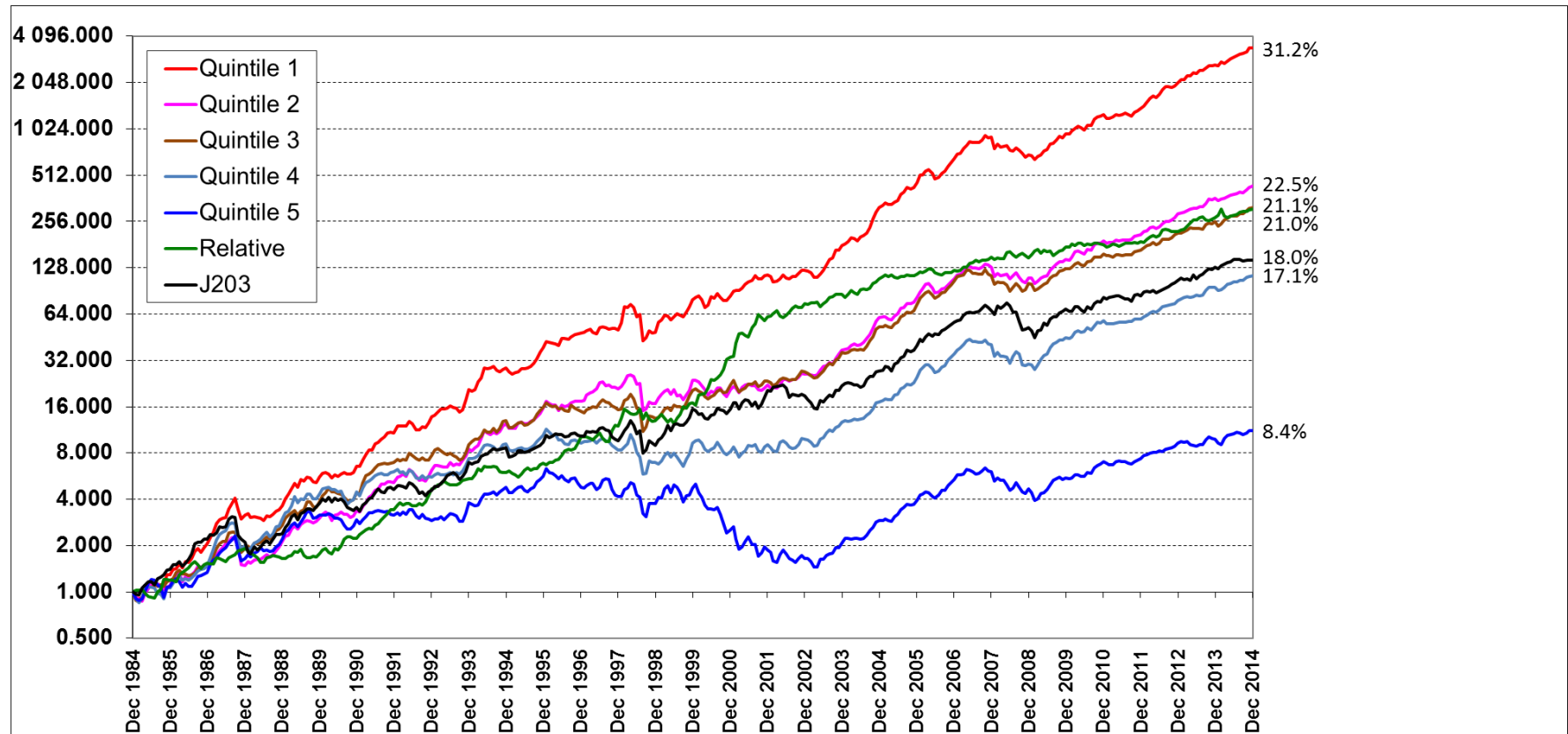
Earnings Yield		Market-To-Book		Company Size	
Weighting	Return	Weighting	Return	Weighting	Return
0%	30.8%	0%	31.3%	0%	34.3%
10%	30.5%	10%	30.3%	10%	31.8%
20%	30.0%	20%	30.1%	20%	31.9%
30%	33.0%	30%	30.5%	30%	32.5%
40%	34.3%	40%	30.6%	40%	33.9%
50%	32.7%	50%	29.8%	50%	33.2%
60%	31.9%	60%	28.6%	60%	33.1%
70%	31.6%	70%	27.9%	70%	31.1%
80%	30.5%	80%	28.4%	80%	30.6%
90%	29.1%	90%	28.6%	90%	30.9%
100%	28.7%	100%	28.0%	100%	31.4%
110%	29.4%	110%	27.8%	110%	29.9%
120%	29.0%	120%	27.5%	120%	29.4%
130%	29.2%	130%	26.7%	130%	28.3%
140%	29.0%	140%	27.1%	140%	27.7%
150%	29.0%	150%	26.3%	150%	27.2%

160%	29.0%	160%	26.3%	160%	27.3%
170%	29.4%	170%	25.7%	170%	27.2%
180%	29.2%	180%	25.7%	180%	27.0%
190%	28.7%	190%	25.0%	190%	27.3%
200%	27.7%	200%	25.5%	200%	27.2%

In the outputs, seen in Table 49, the returns are colour-coded, with the darkest green representing the highest returns and the darkest red indicating the lowest returns. Given these outputs the appropriate weightings would be momentum 12 months 100%, earnings yield 40%, market-to-book 0% and company size (represented by market capitalisation) 0%. Once these were rebased to ensure the total weighting was 100% it equated to momentum 12 months 71.43%, earnings yield 28.57%, market-to-book 0% and company size 0%.

Using these new weightings, the returns per quintile were again generated which led to the trend lines seen in Figure 11.

Figure 11: Optimised Returns Score Quintile Returns for Non-Resources



As can be seen the optimised weightings gave a higher return for quintile 1 of the optimised returns score, 31.2%, whilst the quintiles returns were in the descending order from quintile 1 through to quintile 5.

Whilst the quintiles visually appeared to have significantly different returns this was tested statistically at a 95% level of certainty. The first step in this testing was to generate further descriptive statistics, shown in Table 50, which gave a clearer indication of the apparent relationship once the returns had been made relative to the market returns over the same period.

Table 50: Descriptive Statistics for Optimised Returns for Non-Resources

Quintile	Number of Measures	Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval		Min.	Max
					Lower	Upper		
1	120	0.029	0.082	0.007	0.014	0.044	-0.249	0.268
2	120	0.011	0.080	0.007	-0.004	0.025	-0.238	0.228
3	120	0.007	0.082	0.008	-0.008	0.022	-0.232	0.287
4	120	-0.001	0.093	0.008	-0.017	0.016	-0.216	0.375
5	120	-0.019	0.092	0.008	-0.036	-0.002	-0.251	0.257

Thereafter, as the first phase of the inferential statistics, the homogeneity of the variances was tested as this is a requirement for an ANOVA to be reliable. The outcome of this test is shown in Table 51.

Table 51: Optimised Returns Test for Homogeneity of Variances for Non-Resources

Levene Statistic	df1	df2	Sig.
0.919	4	595	0.452
* indicates significance at a 95% level.			

As seen, the Levene's test was not significant, thus, the ANOVA was computed, as seen in Table 52 below.

Table 52: Optimised Returns ANOVA for Non-Resources

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	0.146	4	0.037	4.948	0.001*
Within Groups	4.403	595	0.007		
Total	4.550	599			

* indicates significance at a 95% level.

The results of the ANOVA showed that a statistically significant difference existed between the quintiles. The exact nature of the difference was seen through the use of the Tukey post hoc test as seen in Table 53 below.

Table 53: Optimised Returns Tukey Post Hoc Tests for Non-Resources

Quintile	Comparison Quintiles	Mean Difference	Std. Error	Sig.	95% Confidence Interval	
					Lower	Upper
1	2	0.019	0.011	0.454	-0.012	0.049
	3	0.022	0.011	0.267	-0.008	0.053
	4	0.030	0.011	0.061	-0.001	0.060
	5	0.048	0.011	0.000*	0.018	0.078
2	1	-0.019	0.011	0.454	-0.049	0.012
	3	0.004	0.011	0.997	-0.027	0.034
	4	0.011	0.011	0.858	-0.019	0.041
	5	0.030	0.011	0.061	-0.001	0.060
3	1	-0.022	0.011	0.267	-0.053	0.008
	2	-0.004	0.011	0.997	-0.034	0.027
	4	0.007	0.011	0.964	-0.023	0.038
	5	0.026	0.011	0.137	-0.005	0.056
4	1	-0.030	0.011	0.061	-0.060	0.001
	2	-0.011	0.011	0.858	-0.041	0.019
	3	-0.007	0.011	0.964	-0.038	0.023
	5	0.019	0.011	0.455	-0.012	0.049

5	1	-0.048	0.011	0.000*	-0.078	-0.018
	2	-0.030	0.011	0.061	-0.060	0.001
	3	-0.026	0.011	0.137	-0.056	0.005
	4	-0.019	0.011	0.455	-0.049	0.012

Thereafter, inferential statistics were employed in the form of a multiple regression analysis, however, to determine the order in which to enter the independent variables, the R^2 , explanatory power, was determined for each of the individual time percentages spent in each ORS quintile against the eventual returns. These are seen in Table 54, sorted according to the R^2 s. The gradient slope simply indicates the direction of the explanatory power

Table 54: Explanatory Power- Individual Quintiles for Non-Resources

Time Spent per Quintile	Gradient Slope	R^2
Quintile 5	-0.45	0.27
Quintile 1	0.28	0.15
Quintile 4	-0.49	0.13
Quintile 2	0.41	0.11
Quintile 3	0.06	0.00

Given those results, the quintiles were entered into the multiple regression calculations in the sequence of quintile 5, quintile 1, quintile 4, quintile 2 and quintile 1.

This resulted in the generation of the models, as seen in Table 55.

Table 55: Multiple Regression Models for Non-Resources

Model Iteration	R^2	R^2 Adjusted	Std. Error	Change Statistics				
				R^2 Change	F Change	df1	df2	Sig.
1	0.265	0.259	0.107	0.265	40.462	1	112	0.000*

2	0.315	0.302	0.104	0.049	8.002	1	111	0.006*
3	0.367	0.350	0.101	0.052	9.062	1	110	0.003*
4	0.367	0.344	0.101	0.000	0.029	1	109	0.866
5	Not computed due to no change in explanatory power.							
* indicates significance at a 95% level.								

As seen in Table 55, the third model had the greatest R^2 adjusted, signalling that it would be the best at explaining variation in the total population. Furthermore, it was the last model where the addition of new measures of time spent in a quintile, specifically quintile 4, had a significant effect on the explanatory power, $p = 0.003$.

Therefore, the results shown below were for the third model, as seen in Table 56.

Table 56: Semi-Final Multiple Regression Model for Non-Resources

Variables/ Constants	Unstandardized Coefficients		t	Sig.	95% Confidence Interval		Collinearity Statistics	
	β	Std. Error			Lower	Upper	Tolerance	VIF
Constant	0.360	0.042	8.584	0.000*	0.277	0.444		
Time in Quintile 5	-0.413	0.072	-5.738	0.000*	-0.555	-0.270	0.866	1.155
Time in Quintile 1	0.040	0.074	0.539	0.591	-0.107	0.186	0.565	1.770
Time in Quintile 4	-0.387	0.128	-3.010	0.003*	-0.641	-0.132	0.634	1.578
* indicates significance at a 95% level.								

Given that the time in quintile 1 was not found to be significant, $p = 0.591$, this variable was removed and the model was rerun giving the results as shown in Table 57 and Table 58 below.

Table 57: Final Multiple Regression R² for Non-Resources

R ²	R ² Adjusted	Std. Error
0.365	0.354	0.100

Table 58: Final Multiple Regression Model for Non-Resources

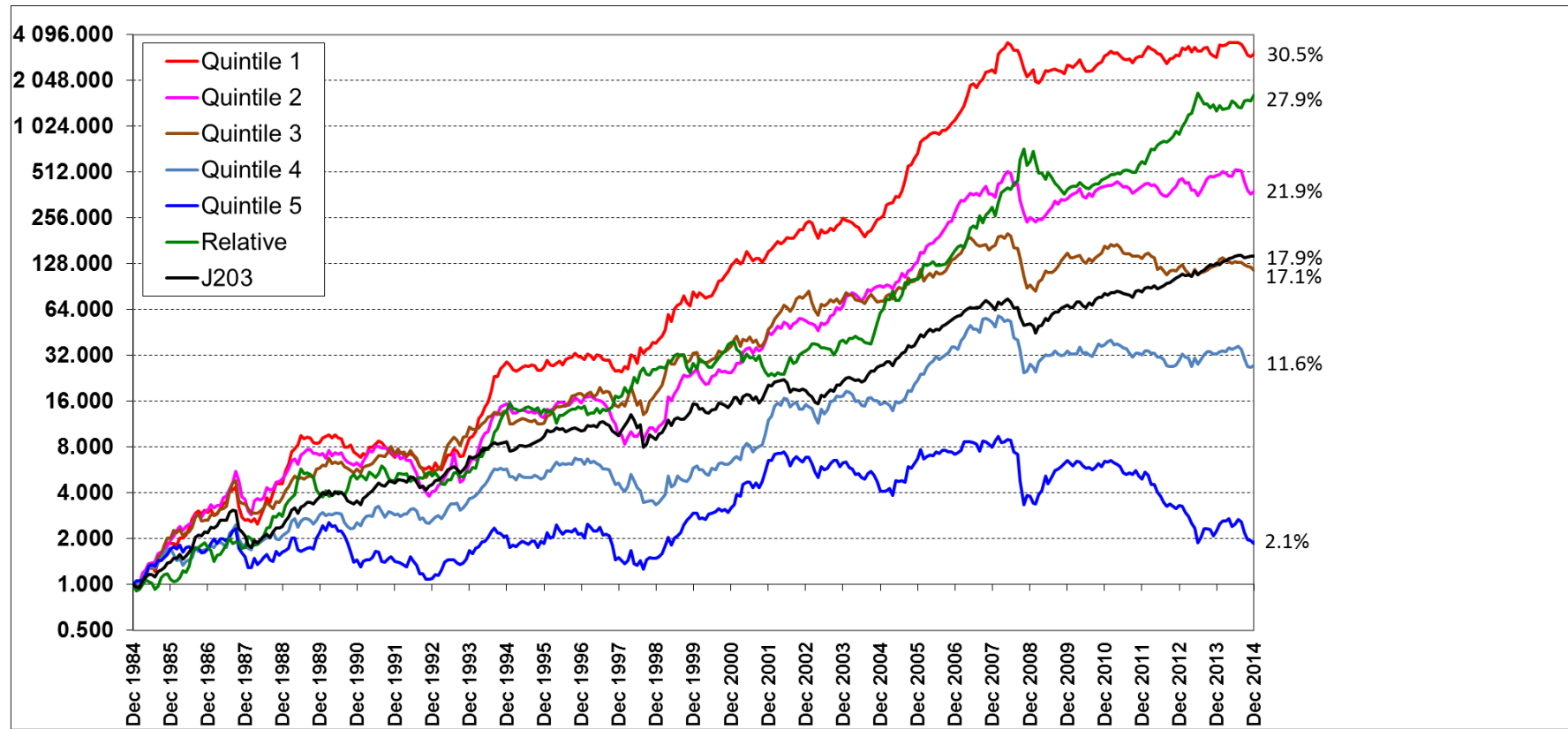
Variables/ Constants	Unstandardized Coefficients		t	Sig.	95% Confidence Interval		Collinearity Statistics	
	β	Std. Error			Lower	Upper	Tolerance	VIF
Constant	0.379	0.024	15.880	0.000*	0.332	0.426		
Time in Quintile 5	-0.427	0.067	-6.361	0.000*	-0.560	-0.294	0.990	1.010
Time in Quintile 4	-0.428	0.102	-4.179	0.000*	-0.631	-0.225	0.990	1.010

* indicates significance at a 95% level.

5.4.4.6.2 Resource Analysis

For the resources a similar process was followed to that of the non-resources, by firstly generating the returns that each unoptimised returns score would have garnered if formed into a portfolio utilising equal weighting of the styles. The results of this can be seen in Figure 12.

Figure 12: Unoptimised Returns Score Quintile Returns for Resources



Even with no optimisation performed on the weightings of constituent styles of the returns score the quintiles perform as designed in descending order from quintile 1 through to quintile 5.

Thereafter, optimisation was performed by holding momentum over the prior 12 months constant at 100%, due to the strong relationship with returns observed in Figure 9 and Table 47, and optimising the weights of the remaining styles. This led to the weighting, as shown in Table 59.

Table 59: Optimisation Outputs for Resources

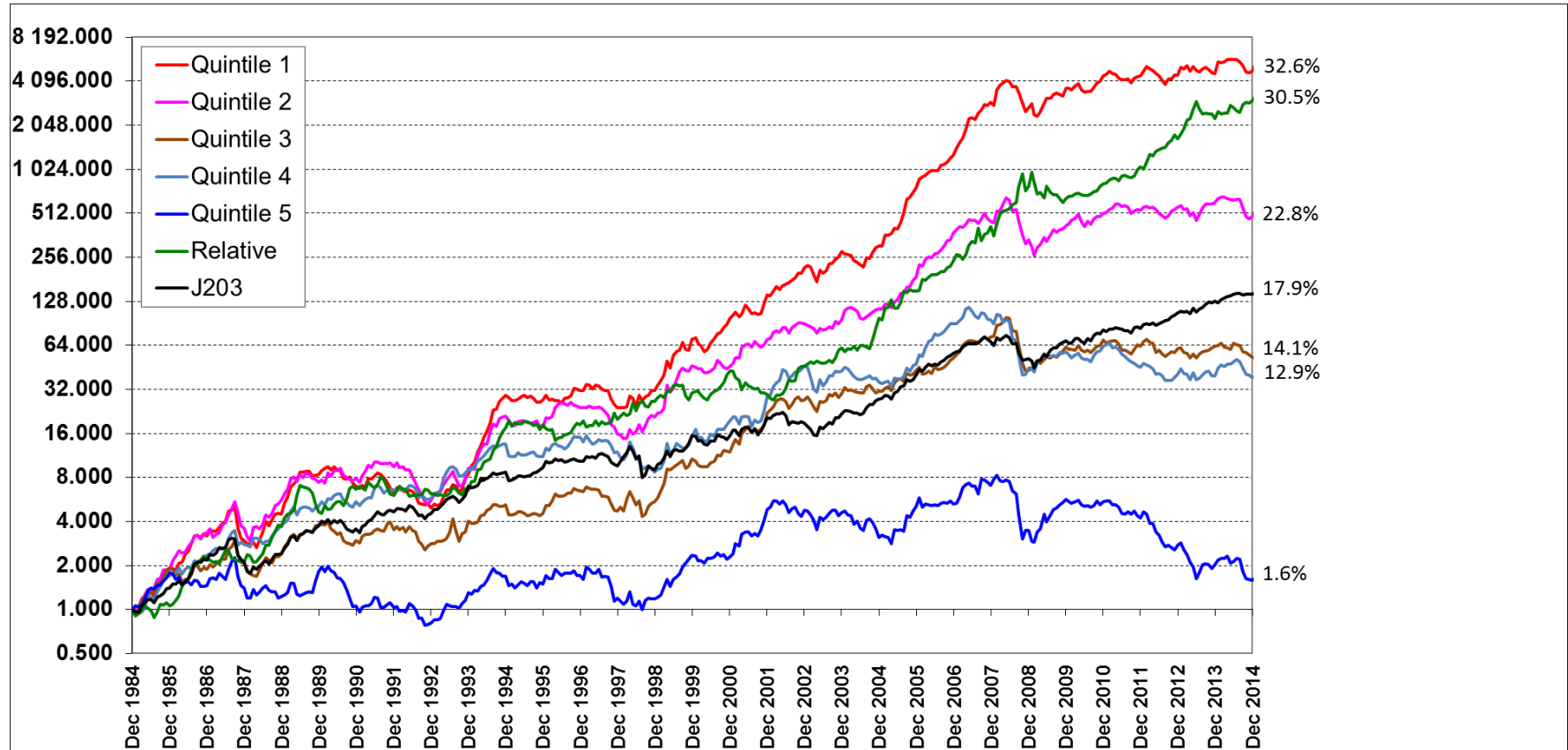
Earnings Yield		Market-To-Book		Company Size	
Weighting	Return	Weighting	Return	Weighting	Return
0%	23.9%	0%	25.3%	0%	27.7%
10%	22.9%	10%	25.3%	10%	27.6%
20%	23.3%	20%	25.7%	20%	27.1%
30%	24.2%	30%	25.8%	30%	26.6%
40%	23.8%	40%	26.9%	40%	26.8%
50%	25.2%	50%	27.3%	50%	27.7%
60%	25.5%	60%	27.9%	60%	28.4%
70%	25.6%	70%	27.1%	70%	28.3%
80%	26.4%	80%	26.4%	80%	28.1%
90%	26.9%	90%	26.7%	90%	28.7%
100%	27.6%	100%	28.3%	100%	28.3%
110%	27.4%	110%	27.9%	110%	26.5%
120%	27.4%	120%	27.8%	120%	25.1%
130%	27.5%	130%	27.6%	130%	25.2%
140%	28.3%	140%	27.0%	140%	25.3%
150%	27.6%	150%	26.9%	150%	24.9%

160%	26.9%	160%	26.5%	160%	24.8%
170%	26.4%	170%	26.8%	170%	25.1%
180%	26.3%	180%	26.5%	180%	24.4%
190%	27.0%	190%	26.3%	190%	24.1%
200%	26.5%	200%	25.9%	200%	24.1%

In the outputs, seen in Table 59, the returns are colour-coded, with the darkest green representing the highest returns and the darkest red indicating the lowest returns. Given these outputs, the appropriate weightings would be momentum 12 months 100% (fixed prior to the optimisation), earnings yield 140%, market-to-book 100% and company size (represented by market capitalisation) 90%. Once these were rebased to ensure the total weighting was 100% it equated to momentum 12 months 23.26%, earnings yield 32.56%, market-to-book 23.26% and company size 20.93%.

Using these new weightings, the returns per quintile were again generated which gave rise to the trend lines seen in Figure 13.

Figure 13: Optimised Returns Score Quintile Returns for Resources



As can be seen the optimised weightings gave a higher return for quintile 1 of the optimised returns score, whilst the quintiles returns remained in the descending order from quintile 1 through to quintile 5.

Whilst the quintiles visually appeared to have significantly different returns this was tested statistically at a 95% level of certainty. The first step in this testing was to generate further descriptive statistics, shown in Table 60, which gave a clearer indication of the apparent relationship once the returns had been made relative to the market returns over the same period.

Table 60: Descriptive Statistics for Optimised Returns for Resources

Quintile	Number of Measures	Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval		Min.	Max
					Lower	Upper		
1	120	0.049	0.106	0.010	0.030	0.068	-0.318	0.342
2	120	0.027	0.148	0.014	-0.000	0.053	-0.377	0.378
3	120	0.006	0.166	0.015	-0.024	0.036	-0.620	0.390
4	120	0.003	0.159	0.014	-0.026	0.032	-0.633	0.447
5	120	-0.021	0.171	0.016	-0.052	0.010	-0.462	0.488

Thereafter, as the first phase of the inferential statistics, the homogeneity of the variances was tested as this is a requirement for an ANOVA to be reliable. The outcome of this test is shown in Table 61.

Table 61: Optimised Returns Test for Homogeneity of Variances for Resources

Levene Statistic	df1	df2	Sig.
6.795	4	595	0.000*
* indicates significance at a 95% level.			

As seen, the Levene's test was significant, indicating probable heterogeneity of variances, thus, the ANOVA was replaced by the Welch test for this specific optimised returns score ranked analysis. The results of the Welch test are shown in Table 62 below.

Table 62: Optimised Returns Welch's Test for Resources

Welch Statistic	df1	df2	Sig.
4.576	4	294.245	0.001*
* indicates significance at a 95% level.			

The results of the Welch test showed that a statistically significant difference existed between the quintiles. The exact nature of the difference was seen through the use of the Tukey post hoc test as seen in Table 63 below.

Table 63: Optimised Returns Tukey Post Hoc Tests for Resources

Quintile	Comparison Quintiles	Mean Difference	Std. Error	Sig.	95% Confidence Interval	
					Lower	Upper
1	2	0.022	0.020	0.790	-0.031	0.076
	3	0.043	0.020	0.182	-0.011	0.097
	4	0.046	0.020	0.131	-0.008	0.100
	5	0.070	0.020	0.003*	0.017	0.124
2	1	-0.022	0.020	0.790	-0.076	0.031
	3	0.021	0.020	0.824	-0.033	0.074
	4	0.024	0.020	0.742	-0.030	0.077
	5	0.048	0.020	0.104	-0.006	0.101
3	1	-0.043	0.020	0.182	-0.097	0.011
	2	-0.021	0.020	0.824	-0.074	0.033
	4	0.003	0.020	1.000	-0.051	0.056
	5	0.027	0.020	0.639	-0.026	0.081
4	1	-0.046	0.020	0.131	-0.100	0.008
	2	-0.024	0.020	0.742	-0.077	0.030
	3	-0.003	0.020	1.000	-0.056	0.051
	5	0.024	0.020	0.732	-0.029	0.078
5	1	-0.070	0.020	0.003*	-0.124	-0.017
	2	-0.048	0.020	0.104	-0.101	0.006
	3	-0.027	0.020	0.639	-0.081	0.026

	4	-0.024	0.020	0.732	-0.078	0.029
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Thereafter, inferential statistics were employed in the form of a multiple regression analysis. However, to determine the order in which to enter the independent variables the R^2 , explanatory power, was determined for each of the time percentages spent in each quintile against the eventual returns. These are seen in Table 64, sorted according to the R^2 s. The gradient slope simply indicated the direction of the explanatory power.

Table 64: Explanatory Power- Individual Quintiles for Resources

Time Spent per Quintile	Gradient Slope	R^2
Quintile 1	0.10	0.04
Quintile 3	-0.13	0.02
Quintile 5	-0.04	0.01
Quintile 4	-0.05	0.00
Quintile 2	-0.02	0.00

Given those results, the quintiles were entered into the multiple regression calculations in the sequence of quintile 1, quintile 3, quintile 5, quintile 4 and quintile 2.

This resulted in the generation of the models, as seen in Table 65.

Table 65: Multiple Regression Models for Resources

Model Iteration	R^2	R^2 Adjusted	Std. Error	Change Statistics				
				R^2 Change	F Change	df1	df2	Sig.
1	0.043	0.002	0.134	0.043	1.039	1	23	0.319
2	0.046	-0.041	0.137	0.003	0.061	1	22	0.807
3	0.046	-0.090	0.140	0.000	0.003	1	21	0.955
4	0.067	-0.120	0.142	0.021	0.443	1	20	0.513

5	Not computed due to no change in explanatory power.
* indicates significance at a 95% level.	

As seen in Table 65, none of the models made a significant change as time spent in the various ORS quintiles was added into the model with $p = 0.319$, $p = 0.807$, $p = 0.955$ and $p = 0.513$.

Given this lack of a statistically significant model, the testing of the models was abandoned at this point, and no further analysis of the multiple regression models was warranted.

Chapter 6 Discussion of Results

6.1 Discussion of the Original CAPM

In Chapter 2, numerous researchers were cited who supported the use of the CAPM in international markets, based on their empirical findings. From Nikolaos (2009) who found it applicable for the financial markets in the United Kingdom to Fama and MacBeth (1973) who had similar findings using American financial data.

Furthermore, it was found in Chapter 2, that the CAPM was not only empirically supported in developed markets, but also in emerging markets, such as South Africa. Initially, Bradfield et al. (1988) found the CAPM to hold in South African conditions. Van Rhijn (1995) also found this to be the case in his research.

However, not all of the researchers found supporting evidence for the CAPM. Fama and French (1992) found that using empirical data from American financial markets did not support the use of the CAPM. Similarly, Damodaran (2012) found that, even twenty years after Fama and French's research, the CAPM still did not apply. This was also found to be the case in Australia as shown by the research of Faff (2001).

In South Africa, Van Rensburg and Robertson (2003) and Strugnell et al. (2011) found the CAPM did not apply to the empirical data observed. Ward and Muller (2012, 2015b) also found the CAPM not to be applicable in South Africa.

Based on these conflicting research findings the exact outcome of this research would not have been easily predicted, but a discussion of each of the specific hypotheses tested is conducted below.

6.1.1 Discussion of Hypothesis $H1a_0$

The null hypothesis stated that the original CAPM held true for the South African financial market. Thus, that expected returns on an asset, or portfolio of assets, could be predicted through analysing the interaction between the risk free rate (R_f), given by the average treasury bill rate at the time, the relative risk of the asset, or portfolio of assets, of interest (β_i) and the expected return on the portfolio of all the shares in the market ($E(\tilde{R}_m)$). The alternative hypothesis stated that the CAPM did not act as a statistically significant predictor of expected returns for the South African market. For this specific test a 24 month time horizon was utilised to calculate the betas.

$$H1a_0: E(\tilde{R}_i) = R_f + \beta_i[E(\tilde{R}_m) - R_f]$$

$$H1a_A: E(\tilde{R}_i) \neq R_f + \beta_i[E(\tilde{R}_m) - R_f]$$

As evidenced in the preamble to this section, the research into whether or not the CAPM was applicable in any context, including South Africa, was particularly inconclusive, so a clear prediction for the outcome of this hypothesis test would not have been easily made.

Based on the descriptive statistical results seen in Table 1, the 14 time periods tested all had correlations between the CAPM predicted returns and the actual returns that varied from the expected correlation of one. In nine of the 14 time periods the correlation actually turned out to be negative, rather than a positive one, which may have implied an inverse relationship between risk and return. These initial findings did not appear to support the relationship claimed by the null hypothesis.

Furthermore, as seen in Appendix 2, graphically none of the graphs showed a scattering of the data points along the perfect correlation line shown in red. As none of the graphs showed the data points clustered tightly around the correlation line, the likelihood that the null hypothesis held appeared to be low.

An additional point of interest is that the CAPM predicted results showed a far narrower range of predicted results. This difference in range width between the predicted and actual returns also made a perfect correlation, as claimed by the null hypothesis, distinctly unlikely.

The fact that the CAPM predicted results were almost all positive, due to the nature of the model, where only a highly negative beta would predict negative returns also meant that a perfect correlation was unlikely, as the actual results included many negative returns.

Progressing to inferential statistics, the individual time periods were first tested to establish if the null hypothesis appeared to hold for each of the periods in isolation. These results, seen in Table 2, showed that of the 14 time periods 12 showed that there was a statistically significant difference between the CAPM predicted and actual returns. This too suggested that the overall null hypothesis seemed unlikely to apply. One point worth mentioning here is that the number of shares tested in

each period, namely 160, ensured that no survivorship bias could influence the results as each share's performance was evaluated.

Finally, the null hypothesis itself was tested, the results of which can be seen in Table 3. These results showed on average, that the CAPM predicted higher returns on the equity (mean = 0.165, std. error = 0.001), than the actual returns (mean = 0.157, std. error = 0.008). This difference, 0.009, 95% confidence interval [-0.007, 0.024], was not significant $t(2239) = 1.088$, $p = 0.276$, but represented an extremely small effect of, $d = 0.024$. Thus, the null hypothesis could not be rejected.

The extremely small effect combined with the fact that 12 of the time series saw the difference between the actual and predicted results as significant raised some concerns around the potential for a type II error, which is when an effect is rejected when it may in fact exist (Field, 2013). These concerns were further intensified when the descriptive and graphical test results were examined as they too suggested that the null hypothesis should likely be rejected.

Thus, in conclusion, the null hypothesis was not rejected, however, it should be viewed with a large amount of scepticism. Thus, any application of the original CAPM with a 24 month beta look-back period should be conducted with due concern for the possibility that a type II error had occurred. This likely supported the research of Strugnell et al. (2011), Van Rensburg and Robertson (2003) and Ward and Muller (2012, 2015b), although was unable to completely reject the findings of Bradfield et al. (1988) and van Rhijn (1995) due to the failure to reject the null hypothesis.

6.1.2 Discussion of Hypothesis $H1b_0$

Jagannathan and Wang (1996) expounded upon the perils of not adjusting for the time variations in the beta of a certain stock, and making the assumption of constant betas. As they pointed out market shocks would affect certain industries more than others, and hence shares in the most affected industries would have increases in their betas as their performance would be more affected than that of the market as a whole. They also pointed out that a company in financial distress would be plunged even further into distress during a recession making them more reliant on leverage for their financing needs and in all probability driving their betas upwards (Jagannathan & Wang, 1996). All of these factors fuelled the need to adjust betas as time progressed.

Ferson and Korajczyk (1995) empirically proved that models that assumed a constant beta performed poorly in comparison to models that adjusted the time-period over which they measured their betas.

In deference to this prior research, this study employed the techniques used by Ward and Muller (2012) to also test a dynamic beta over a varied time period. Hence, for this hypothesis the previous 60 months of returns were used to calculate the beta to be applied. This allowed for the testing of whether the beta time period used for a dynamic beta, known as the look-back period, brought about different results in testing the original CAPM.

Thus, the null hypothesis was identical to that depicted in $H1a_0$, however, the 24 month time horizon for beta calculations was replaced by a 60 month time horizon. The alternative hypothesis was similar to $H1a_A$, except that its time horizon was also increased to 60 months.

$$H1b_0: E(\tilde{R}_i) = R_f + \beta_i[E(\tilde{R}_m) - R_f]$$

$$H1b_A: E(\tilde{R}_i) \neq R_f + \beta_i[E(\tilde{R}_m) - R_f]$$

The descriptive statistics, shown in Table 4, indicated what appeared to be noteworthy differences between the observed correlations between the actual results and those predicted by the original CAPM utilising a conventional 60 month look-back beta. The correlations in all 5 of the time periods observed were found to be negative, indicating an inverse correlation between the CAPM's predictions and the actual observed returns, and casting doubts on the ability of the null hypothesis to apply.

These differences were also highly evident when depicted graphically in Appendix 3, where each of the time periods was graphed to show the correlation between the CAPM predicted returns and the actual returns. Here too, each graph showed the 45 degree perfect correlation line in red. Although, none of the graphs showed a clustering around the correlation line indicating that the null hypothesis was unlikely to hold.

Yet again, the predicted CAPM values appeared to have a far smaller range than the actual returns, which appeared unlikely to support the relationship claimed by the null hypothesis.

The inferential statistical testing of each of the individual time periods, as seen in Table 5, showed that in four of the five tested time periods the CAPM predicted returns were significantly different from the actual returns observed. This made the overall applicability of the null hypothesis unlikely. However, this was tested in Table 6.

The results of this test showed that on average, the CAPM predicted higher returns on the equity (mean = 0.168, std. error = 0.001), than the actual returns (mean = 0.094, std. error = 0.008). This difference, 0.074, 95% confidence interval [0.058, 0.090], was significant $t(799) = 9.323$, $p = 0.000$, and represented a medium sized effect of, $d = 0.343$. Thus, the null hypothesis was rejected.

This was in line with the findings of the descriptive and graphical tests conducted, and supported the cessation of use of the original CAPM, with a 60 month conventional beta, to predict the cost of equity. Whilst the use of a different beta look-back period had not brought about markedly different test results as suggested by Ferson and Korajczyk (1995) and Jagannathan and Wang (1996), the rejection of the null hypothesis was in line with the research of Strugnell et al. (2011), Van Rensburg and Robertson (2003) and Ward and Muller (2012, 2015b).

6.1.3 Discussion of Hypothesis $H1c_0$

Dimson (1979) and Scholes and Williams (1977) identified that infrequent trading could cause erroneous betas to be calculated, and as such they made proposals for alternative methods of calculating betas that accounted for infrequent trading.

Ward and Muller (2012) applied the Dimson' beta with four lagged periods and one leading period. This research employed the same approach, and for this specific hypothesis a 24 month period was used in the Dimson' beta calculations. However, Ward and Muller (2012) did highlight that although it was pragmatic to employ the Dimson' beta, it was unlikely to result in markedly different results from a conventional beta due to the highly traded nature of the top 160 shares on the JSE.

As such, it was expected that the results for the testing of hypothesis $H1c_0$ would be the same as that for hypothesis $H1a_0$ above.

For this null hypothesis the time horizon remained at 24 months for the beta calculations, with four lagged periods and one leading period. The alternative

hypothesis was the same as $H1a_A$, simply adjusted to utilise the Dimson' beta calculation over a 24 month time horizon.

$$H1c_0: E(\tilde{R}_i) = R_f + \beta_i[E(\tilde{R}_m) - R_f]$$

$$H1c_A: E(\tilde{R}_i) \neq R_f + \beta_i[E(\tilde{R}_m) - R_f]$$

To initially cursorily test this hypothesis, descriptive statistics were also generated to see if a correlation between the CAPM predicted results, using the Dimson' 24 month beta correlated with the actual eventual returns. The results of this test can be seen in Table 7, where what appeared to be noteworthy differences could be seen between the observed correlation between the actual results and those predicted by the original CAPM utilising a 24 month look-back Dimson' beta. The correlations in 11 of the 14 time periods observed were found to be negative, indicating an inverse correlation between the CAPM's predictions and the actual observed returns, rendering the null hypothesis unlikely to hold.

These differences were also highly evident when depicted graphically in Appendix 4, where each of the time periods was graphed to show the correlation between the CAPM predicted returns and the actual returns. Here too, each graph showed the 45 degree perfect correlation line in red, but the failure of the data points to congregate around this line suggested that the null hypothesis was likely to be rejected.

Another notable observation, was that the Dimson' beta seemed to create a wider dispersion of CAPM predicted results than that rendered by the conventional beta calculation as seen in Appendix 2. This was relevant as a wider dispersion meant that the CAPM predicted results were more likely to match the wider dispersion of the actual results. However, the failure of the data points to fall on or near the correlation line did still not appear to support the null hypothesis.

Following this, inferential statistics were applied to each of the individual time periods, as seen in Table 8. Out of the 14 time periods analysed, 11 of them showed significant differences from the CAPM predicted results at a 95% confidence level. However, the three periods in which the CAPM with a 24 month look-back period Dimson' beta could not be rejected appeared to show a strong likelihood that the CAPM predicted results and the actual results were drawn from the same population, with the results from the final individual time period showing a $p=0.983$, hence a very strong likelihood that the results were from the identical

population. Thus, a prediction of whether the null hypothesis would be supported was not easily made, although it appeared most likely that the null hypothesis would be rejected as 11 of the periods found that the CAPM predicted returns and actual returns significantly differed.

When the null hypothesis was tested for the whole time period, it was found that on average, the CAPM predicted higher returns on the equity (mean = 0.174, std. error = 0.002), than the actual returns (mean = 0.157, std. error = 0.008). This difference, 0.017, 95% confidence interval [0.001, 0.033], was significant $t(2239) = 2.089$, $p = 0.037$, but represented an extremely small effect of, $d = 0.046$. Thus, the null hypothesis was rejected.

It was notable that $H1a_0$ was not rejected, whilst $H1c_0$ was rejected which is not aligned to what was predicted by Ward and Muller (2012). However, this may in fact lend credence to the suggestion that a type II error occurred in the test of the null hypothesis $H1a_0$.

In any event, this result suggests that the CAPM should not be employed to predict the cost of equity, even if illiquidity is adjusted for through the use of the Dimson' 24 month beta. This was in line with the findings of Strugnell et al. (2011), Van Rensburg and Robertson (2003) and Ward and Muller (2012, 2015b).

6.1.4 Discussion of Hypothesis $H1d_0$

As previously cited, Jagannathan and Wang (1996) and Ferson and Korajczyk (1995) found that for the most thorough results the time periods used to calculate the betas should be varied, as well as accounting for trade illiquidity (Dimson, 1979; Scholes & Williams, 1977).

Again, Ward and Muller (2012) suggested that controlling for illiquidity was unlikely to result in meaningful differences in results from the conventional beta. Given this, it was expected that null hypothesis $H1d_0$ would not have a markedly different test outcome from null hypothesis $H1b_0$. Given that $H1b_0$ was rejected it was reasonably expected that $H1d_0$ would also be rejected.

To test this, the descriptive statistics were computed, as seen in Table 10. What appeared to be noteworthy differences between the observed correlation between the actual results and those predicted by the original CAPM, utilising a 60 month look-back Dimson' beta, were observed. The correlations in all five of the time

periods observed were found to be negative, indicating an inverse correlation between the CAPM's predictions and the actual observed returns. This suggested that the null hypothesis was unlikely to be supported.

These differences were also highly evident when depicted graphically in Appendix 5, where each of the time periods was graphed to show the correlation between the CAPM predicted returns and the actual returns. Here too, each graph showed the 45 degree perfect correlation line in red. Unlike with the 24 month look-back period Dimson' beta, the Dimson' beta utilising a 60 month look-back period did not result in a visibly more dispersed range of predicted results than the conventional beta equivalent as seen in Appendix 3. The combination of this narrowed range and the data points not being plotted on or near the correlation line also indicated that the null hypothesis may well have been rejected.

Using inferential statistics, Table 11 was produced showing that in four out of five of the time periods tested, a significant difference between the CAPM predicted results and the actual results was found, suggesting that the null hypothesis was unlikely to be supported. However, hypothesis $H1d_0$ referred to the entire time period as seen in Table 12.

The results of the inferential test for the whole period was that on average, the CAPM predicted higher returns on the equity (mean = 0.173, std. error = 0.002), than the actual returns (mean = 0.094, std. error = 0.008). This difference, 0.079, 95% confidence interval [0.063, 0.094], was significant $t(799) = 9.578$, $p = 0.000$, and represented a medium sized effect of, $d = 0.366$. Thus, the null hypothesis was rejected.

The rejection of the null hypothesis was consistent with the descriptive and graphical test results, as well as being consistent with, and producing the same result that was found, when hypothesis $H1b_0$ was tested as suggested by Ward and Muller (2012).

This rejection meant that the CAPM with a Dimson' beta utilising a 60 month look-back period should not be applied to calculate the cost of equity capital. This too was in line with the research of Strugnell et al. (2011), Van Rensburg and Robertson (2003) and Ward and Muller (2012, 2015b) on the applicability of the CAPM in South African financial markets.

6.2 Discussion of the Black's CAPM

The Black's CAPM was widely utilised, and supported, in research on the American financial markets by Fama and MacBeth (1973) and Morgan (1975). However, it only recently became more prevalent in South African research as Strydom and Charteris (2013) and Ward and Muller (2015b) used the Black's CAPM to empirically test its applicability to the South African market.

The research conducted by Strydom and Charteris (2013), indicated that the CAPM, after being modified to remove the reliance on a risk free proxy, did indeed predict the returns that could be witnessed in the South African financial market from 1993 to 2008, supporting the use of the Black's CAPM to predict returns on equity.

However, Ward and Muller (2015b) found that in their research the empirical data from 1985 to 2014 did not appear to support the applicability of the Black's CAPM to the South African financial markets.

These conflicting findings made it unclear what was to be expected in the tests of the Black's CAPM. Furthermore, as with the original CAPM hypotheses the beta look-back period was also varied and the risk of trade illiquidity was also addressed.

6.2.1 Discussion of Hypothesis $H2a_0$

The first null hypothesis in this section of hypotheses stated that Black's CAPM held true for the South African financial market. Thus, that expected returns on an asset, or portfolio of assets, could be predicted through analysing the interaction between the expected returns on a zero-beta portfolio ($E(\tilde{R}_Z)$), the relative risk of the asset, or portfolio of assets, of interest (β_i) and the expected return on the portfolio of all the shares in the market ($E(\tilde{R}_m)$). The alternative hypothesis stated that Black's CAPM did not act as a reliable predictor of expected returns for the South African market. For this specific test a 24 month time horizon was used to calculate the betas.

$$H2a_0: E(\tilde{R}_i) = E(\tilde{R}_Z) + \beta_i[E(\tilde{R}_m) - E(\tilde{R}_Z)]$$

$$H2a_A: E(\tilde{R}_i) \neq E(\tilde{R}_Z) + \beta_i[E(\tilde{R}_m) - E(\tilde{R}_Z)]$$

As evidenced in the previous section the research into whether or not the CAPM was applicable in South Africa was particularly inconclusive. Strydom and Charteris

(2013) supported its applicability whilst Ward and Muller (2015b) opposed its use. Thus, a clear prediction for the outcome of this hypothesis test would not have been easily made.

Based on the descriptive statistical results seen in Table 15, it can be gleaned that there are noteworthy differences between the expected correlation and the observed correlation of the actual returns and those predicted by the Black's CAPM. This suggested that the null hypothesis would likely be rejected.

Nine of the 14 time periods also found a negative correlation with the predicted Black's CAPM results, indicating the possibility of an inverse relationship between the predicted and actual returns. This resulted in a strong possibility that the null hypothesis would not hold.

Another point that was noted was that in the formation of the zero-beta portfolio for the Black's CAPM calculations certain shares were excluded, which did introduce the potential for survivorship bias, and the results should be viewed in this light.

In two of the 14 time periods analysed the risk free rate generated was actually negative which may have more accurately reflected the fluctuating returns of equities. However, as seen in the graphical analysis in Appendix 6, the predicted returns still fell in a far narrower range than the actual returns, despite the increased ability to predict negative returns. This narrow range meant that it was unlikely that the Black's CAPM predicted results and the actual returns were from the same population, hence the likelihood that the null hypothesis would be rejected.

Next, the inferential statistics were performed on each individual time period, with ten of the 14 time periods having significant differences between the Black's CAPM predicted returns and the actual returns, as seen in Table 16. Interestingly, during the period over which Strydom and Charteris (2013) conducted their research, 1993 to 2008, a significant difference was only not detected for the four year period from 31 December 2000 until 31 December 2004. This indicated that it was extremely unlikely that the results would support the findings of Strydom and Charteris (2013), and hence that the null hypothesis was likely to be rejected.

Finally, in the inferential analysis for the whole time period, Table 17, it was found that on average, the Black's CAPM predicted higher returns on the equity (mean = 0.186, std. error = 0.003), than the actual returns (mean = 0.157, std. error = 0.008). This difference, 0.029, 95% confidence interval [0.012, 0.045], was significant

$t(2239) = 3.453$, $p = 0.001$, but represented a very small effect of, $d = 0.079$. Thus, the null hypothesis was rejected.

This rejection of the null hypothesis was in line with the rest of the analyses predictions. However, it was of particular significance as null hypothesis $H1a_0$ was not rejected, albeit with suspicions of a type II error. This implied Black's CAPM had failed to be a better predictor of the cost of capital equity than the original CAPM, given the same look-back period constraints.

Thus, the Black's CAPM using a 24 month look-back period should not be used, and is certainly a no better indicator of equity capital costs than the original CAPM. This was in contrast to the findings of Strydom and Charteris (2013), but wholly in line with the findings of Ward and Muller (2015b).

6.2.2 Discussion of Hypothesis $H2b_0$

As discussed under the analysis of the original CAPM, Ferson and Korajczyk (1995) and Jagannathan and Wang (1996) found strongly that the beta look-back period should be varied as it could impact upon the results obtained in research on the CAPM. Thus, the results could be expected to be markedly different to those obtained using a different time period, such as with hypothesis $H2a_0$.

In deference to this prior research, this study employed the techniques used by Ward and Muller (2012) to also test a dynamic beta over a varied time period. Hence, for this hypothesis the previous 60 months of returns were used to calculate the beta to be applied. This allowed for the testing of whether the beta time period used for a dynamic beta brought about different results in testing from the original CAPM.

Thus, the null hypothesis was identical to that depicted as $H2a_0$, however, the 24 month time horizon for beta calculations was replaced by a 60 month time horizon. The alternative hypothesis was similar to $H2a_A$, except that its time horizon was also increased to 60 months.

$$H2b_0: E(\tilde{R}_i) = E(\tilde{R}_z) + \beta_i[E(\tilde{R}_m) - E(\tilde{R}_z)]$$

$$H2b_A: E(\tilde{R}_i) \neq E(\tilde{R}_z) + \beta_i[E(\tilde{R}_m) - E(\tilde{R}_z)]$$

The descriptive analysis, as seen in Table 18 showed the variables employed in the test of the Black's CAPM utilising a 60 month look-back beta. The first noteworthy

point is the increased presence of potential survivorship bias in the calculation of the minimum variance zero-beta portfolio, seen by the fact that fewer shares were generally utilised to calculate the minimum variance zero-beta portfolio than when a 24 month look-back period was used. This was to be expected as a longer time period under observation meant that there was greater opportunity for a share to leave the exchange.

However, the zero-beta portfolio returned no negative risk free rates, unlike with the 24 month look-back period. All five of the time periods returned a negative actual correlation with the predicted Black's CAPM results, indicating the possibility of an inverse relationship between the predicted and actual results. This indicated that the likelihood of not rejecting the null hypothesis was very low.

The graphical analysis, as seen in Appendix 7, yet again showed that a narrower range of returns had been predicted than what was actually observed. Thus, that the null hypothesis was unlikely to be accepted.

Performing inferential statistical analysis on the individual time periods gave the results seen in Table 19. Of the five time periods analysed, all of them showed significant differences from the Black's CAPM predicted results at a 95% confidence level. This suggested that failure to reject the null hypothesis was unlikely.

Finally, as seen in Table 20, on average, the Black's CAPM predicted higher returns on the equity (mean = 0.147, std. error = 0.001), than the actual returns (mean = 0.101, std. error = 0.008). This difference, 0.046, 95% confidence interval [0.030, 0.062], was significant $t(799) = 5.696$, $p = 0.000$, but represented a small to medium sized effect of, $d = 0.206$. Thus, the null hypothesis was rejected.

This rejection of the null hypothesis was in line with what was predicted by the descriptive and graphical statistical analyses. However, this did not necessarily refute the assertions of Ferson and Korajczyk (1995) and Jagannathan and Wang (1996) that different look-back periods may produce different results, as although both hypotheses $H2a_0$ and $H2b_0$ were both rejected the size of the effects were different.

Irrespective of the time period used for the look-back periods, the eventual recommendation is that the Black's CAPM not be used to cost equity capital, supporting the findings of Ward and Muller (2015b).

6.2.3 Discussion of Hypothesis $H2c_0$

Given the concerns around the illiquid trading of shares identified, and previously researched by Dimson (1979) and Scholes and Williams (1977) this potential illiquid trading was accounted for under this null hypothesis and the following one.

Although, as pointed out by Ward and Muller (2012), through the use of the highly traded top 160 shares, applying the Dimson' beta calculation technique was unlikely to result in distinctly different betas. Hence, the results should have been similar to those for hypothesis $H2a_0$, as the same beta look-back period was employed. Therefore, the prior research, when combined with the test of hypothesis $H2a_0$, suggested that the null hypothesis would be rejected.

The null hypothesis was the same as $H2a_0$, except that the Dimson' beta calculation was performed. The time horizon remained at 24 months for the beta calculations. The alternative hypothesis was the same as $H2a_A$, simply adjusted to utilise the Dimson' beta calculation over a 24 month time horizon.

$$H2c_0: E(\tilde{R}_i) = E(\tilde{R}_z) + \beta_i[E(\tilde{R}_m) - E(\tilde{R}_z)]$$

$$H2c_A: E(\tilde{R}_i) \neq E(\tilde{R}_z) + \beta_i[E(\tilde{R}_m) - E(\tilde{R}_z)]$$

To initially test this hypothesis, descriptive statistics were generated, as seen in Table 21. Again, it should be noted that there was potential survivorship bias in the calculation of the minimum variance zero-beta portfolio. However, there appeared to be marked differences between the expected correlation and the actual correlation of returns, which suggested that the null hypothesis would likely be rejected.

Additionally, 12 out of the 14 time periods produced a negative correlation with the predicted Black's CAPM results, indicating the possibility of an inverse relationship between the predicted and actual results. Thus, it would again be expected that the null hypothesis would be rejected.

As with hypothesis $H2a_A$, in two of the 14 time periods analysed, the risk free rate generated was actually negative which may have more accurately reflected the fluctuating returns on equities. However, as seen in the graphical analysis in Appendix 8, the predicted returns still generally fell in a narrower range than the actual returns, although these did appear to be the widest range of predicted returns found in any of the graphical analyses. This still narrow range meant that it was

unlikely that the Black's CAPM predicted results and the actual returns were from the same population, hence the likelihood that the null hypothesis would be rejected.

The inferential statistics were then calculated for each of the individual time periods, as seen in Table 22. Nine of the 14 periods had significant differences between the Black's CAPM predicted returns and the actual returns. However, it should be noted that there appeared to have been a sustained period between 31 December 2000 and 31 December 2006 where the Black's CAPM did seem to have been a significant measure of the predicted returns. However, the underlying reason for the applicability of the Black's CAPM during these time periods and the others where the predictions were not significantly different are beyond the scope of this paper. However, as nine of the periods exhibited significant differences, the likelihood of rejecting the null hypothesis appeared strong.

The final inferential tests, seen in Table 23, found that on average, the Black's CAPM predicted higher returns on the equity (mean = 0.194, std. error = 0.003), than the actual returns (mean = 0.157, std. error = 0.008). This difference, 0.037, 95% confidence interval [0.020, 0.054], was significant $t(2239) = 4.340$, $p = 0.000$, but represented a small effect of, $d = 0.101$. Thus, the null hypothesis was rejected. This was aligned to the suggestions of the previous tests of this hypothesis.

Therefore, the use of the Black's CAPM with a Dimson' 24 month look back beta would be strongly advised against, as per the findings of both this paper and that of Ward and Muller (2015b).

6.2.4 Discussion of Hypothesis $H2d_0$

As previously referenced, Jagannathan and Wang (1996) and Ferson and Korajczyk (1995) found that for the most thorough results the time periods used to calculate the betas should be varied, as well as accounting for trade illiquidity (Dimson, 1979; Scholes & Williams, 1977).

Again, Ward and Muller (2012) suggested that controlling for illiquidity was unlikely to result in meaningful differences in results from the conventional beta. Given this, it was expected that null hypothesis $H2d_0$ would not have a markedly different test outcome from null hypothesis $H2b_0$. Given that $H2b_0$ was rejected it was reasonably expected that $H2d_0$ would also be rejected.

The hypothesis for this category of testing was the same as $H2c_0$, except that a 60 month time horizon was utilised to account for differences in beta calculations introduced through dissimilar time horizons. Naturally, the alternative hypothesis was identical to $H2c_A$, except that its beta time horizon was adjusted to 60 months too.

$$H2d_0: E(\tilde{R}_i) = E(\tilde{R}_Z) + \beta_i[E(\tilde{R}_m) - E(\tilde{R}_Z)]$$

$$H2d_A: E(\tilde{R}_i) \neq E(\tilde{R}_Z) + \beta_i[E(\tilde{R}_m) - E(\tilde{R}_Z)]$$

To test this, descriptive statistics were generated, as seen in Table 24. Again the first notable point was that the chances for survivorship bias were greatly increased, given the requirement to exclude shares that had not been in existence for the individual time period being reviewed, namely the entire previous 60 months.

However, the zero-beta portfolio returned no negative risk free rates, unlike with the 24 month look-back period. All five of the time periods showed a negative correlation with the predicted Black's CAPM results, indicating the possibility of an inverse relationship between the predicted and actual results. This suggested that the null hypothesis would likely be rejected.

The graphical analysis, seen in Appendix 9, also showed that the Black's CAPM predicted results fell in a far narrower range than the actual results observed, although the ranges appeared to be wider than those produced using the original CAPM with conventional betas. The persistence of narrow predicted returns ranges, albeit marginally wider, suggested that the null hypothesis would likely be rejected.

The first iteration of inferential statistics for this hypothesis, seen in Table 25, showed that of the five time periods analysed, only one of them did not show a significant difference from the Black's CAPM predicted results at a 95% confidence level. This indicated a strong likelihood of rejecting the overall null hypothesis.

The final inferential statistical tests, as seen in Table 26, showed that on average, the Black's CAPM predicted higher returns on the equity (mean = 0.183, std. error = 0.003), than the actual returns (mean = 0.094, std. error = 0.008). This difference, 0.089, 95% confidence interval [0.073, 0.106], was significant $t(799) = 10.568$, $p = 0.000$, but represented a medium to large sized effect of, $d = 0.413$. Thus, the null hypothesis was rejected, in line with the expected findings suggested by the other non-inferential tests conducted on this hypothesis.

Therefore, it is recommended that the Black's CAPM with a Dimson' 60 month look-back beta, not be used for the estimation of the cost of equity capital as per the findings of Ward and Muller (2015b).

6.3 Concluding Thoughts on the CAPM Analyses

For the most part, the research around the relationship between beta and the cost of equity capital was split between three schools of thought. Firstly, there were those researchers who had observed a positive relationship between beta and returns, as claimed by the CAPM. Then there were those researchers whose findings revealed that no relationship existed. Finally, there were those researchers who found the existence of an inverse relationship, and in so doing undermined the central tenet of the CAPM.

Fama and MacBeth (1973), were amongst the first group of researchers, and found that there was a perfectly linear relationship between risk and return. More recently, Fraser, et al. (2004) also found that the beta held a positive relationship to returns.

Amongst the second school of thought were researchers such as Fama and French (1992), who first disproved the relationship between beta and returns using American financial data. In their later research they came to the categorical conclusion that no relationship whatsoever existed between risk and returns as claimed by the CAPM (Fama & French, 2004).

Finally, researchers such as Pettengill et al. (1995) found that high beta shares experienced below market average returns, which was supported by Frazzini and Pedersen (2014) who found that risk adjusted returns dropped as betas rose. This unexpected phenomenon was not only observed using developed markets' data, but also emerging markets', as discovered by Lazar and Yaseer (2010) when they analysed Indian financial data and Ward and Muller (2012) when they analysed South African data.

Given the widely divergent nature of the researchers' results, a prediction around whether the underlying relationship of the CAPM would be supported by this research paper could not be made.

However, given the summarised findings seen in Table 13, Table 14, Table 27 and Table 28, it seemed unlikely with so many of the null hypotheses being rejected across the various time periods, irrespective of the specific version of the CAPM employed, that a positive relationship between risk, represented by beta, and returns would be found as claimed by Fama and MacBeth (1973) and Fraser et al. (2004).

Examination of the graphical plotting of virtual portfolios based on beta, Figure 4, showed that portfolios with lower betas generally outperformed those with higher betas. Of particular interest in that figure was the brown price relative trend line, which clearly showed that the lowest ranked beta portfolio had consistently outperformed the highest beta portfolio across the various time series.

Using inferential statistics in Table 31 and Table 32, it was found that there was a significant effect on returns of the beta score, $F(4, 276.461) = 3.145$, $p=0.015$. This significant linear trend indicated that as the beta increased the returns decreased. The Tukey post hoc analysis showed that there was a significant difference between the highest beta ranked quintile, quintile 1, and quintiles 4 and 5, $p=0.012$ and $p=0.016$ respectively. The other quintiles did not display a statistically significant difference in their means.

Based on this, it can be seen that an inverse relationship did indeed exist between risk, as represented by beta, and the cost of equity capital. This finding supported the findings of Pettengill et al. (1995), Frazzini and Pedersen (2014) and Lazar and Yaseer (2010). From a South African perspective, this finding also supported the findings of Ward and Muller (2012, 2015b).

This finding was of particular significance given the high reported usage of the CAPM within South Africa (Correia & Cramer, 2008; Damodaran, 2012; Harford, 2014). This high usage meant that decisions were being taken assuming the opposite relationship between risk and return from what was empirically found in this research casting significant doubt on the quality of such decisions.

6.4 Discussion of the Alternative Pricing Model

The succeeding discussion is arranged through first discussing the individual styles influence upon the cost of equity capital, if any. Thereafter, the combination of these styles was tested for their significance in predicting the cost of the equity capital.

Hsu and Kalesnik (2014) and Montier (2007) both found that the CAPM was a poor approximation of the empirical reality of equity returns, however, they identified numerous styles that appeared to have a significant influence upon the cost of equity, some of which are analysed below.

6.4.1 Discussion of the Sector Style

Internationally, using Australian financial data, Faff (2001) found that resource shares typically underperformed non-resource shares. This finding was supported in the South African context by the work of Muller and Ward (2013), Van Rensburg and Robertson (2003) and Ward and Muller (2012, 2015b). All of whom found that over a number of years resource shares underperformed non-resource shares.

To test this, the shares were grouped into virtual portfolios of resource and non-resource shares respectively and then plotted as seen in Figure 5. Visually it could be seen that the non-resource shares showed higher returns of 18.95% than the resource shares, 12.28%. The price relative trend line of the difference between the resource shares' and non-resource shares' returns showed that non-resource shares outperformed the resource shares over almost the entire period. This was clearly in line with expectations based on the prior research of Faff (2001), Muller and Ward (2013), Van Rensburg and Robertson (2003) and Ward and Muller (2012, 2015b).

Thereafter, a statistical analysis was performed on the data, as seen in Table 33 and Table 34. The result of this statistical analysis was that on average, non-resource shares gave higher returns over the market (mean = 0.006, std. error = 0.007), than resource shares (mean = -0.005, std. error = 0.009). This difference, 0.011, 95% confidence interval [-0.010, 0.032], was, however, not significant $t(207.909) = 1.042$, $p = 0.298$; nevertheless, a small effect was observed, $d = 0.122$.

So whilst visually appearing to be aligned to the prior research the results of this study show that a statistically significant difference between resource and non-resource shares' returns was not able to be identified. Hence, the prior research of

Faff (2001), Muller and Ward (2013), Van Rensburg and Robertson (2003) and Ward and Muller (2012, 2015b) could not be conclusively supported.

6.4.2 Discussion of the Market-to-Book Style

Fama and French (1992, 2012, 2015) found that over the last 23 years of research one of the styles that had maintained its negative relationship with returns throughout was the market-to-book ratio.

Other researchers such as Asness et al. (2013), confirmed these findings, also using American market data as Fama and French (1992, 2012, 2015) had done.

This phenomenon was observed outside American markets too as shown by Hsu and Kalesnik (2014) who researched the relationship between styles and returns in developed nations, namely the United States of America, the United Kingdom, Europe as a whole and Japan. They too found that market-to-book ratios had a significant relationship with returns on equity.

It appeared that this anomaly was not unique to developed nations as it had also been consistently observed using South African financial data over various time periods (Muller & Ward, 2013; Strugnell et al., 2011; Van Rensburg & Robertson, 2003).

Given this resounding support of a relationship between the market-to-book ratio and the cost of equity it would be expected that this research would also find this negative relationship where low market-to-book ratio shares, or portfolios, would outperform the higher market-to-book ratio financial assets.

Graphically, as seen in Figure 6, the negative relationship between market-to-book ratios and returns appeared to have held over the total time period, however, as seen by the price relative line, in green, this effect may well have ceased to be present since 2004, and may even have become inverted in 2011 and 2012.

Thereafter, the relationship was tested using inferential statistics, Table 37, which showed that there was no significant effect of the market-to-book ratio on equity returns, $F(4, 595) = 1.700, p = 0.148$. This was in contrast to the abundant research, but given that Figure 6's price relative line showed that the effect used to be present, but was no longer, it was understandable that there could be volumes of historical research showing a relationship which no longer existed.

However, whilst finding against the research of Muller and Ward (2013), Strugnell et al. (2011), and Van Rensburg and Robertson (2003), this finding actually corroborated the claim by Muller and Ward (2013) that no style would provide abnormal returns indefinitely as investors would invest in such a manner so as to close the arbitrage opportunity.

6.4.3 Discussion of the Earnings Yield Style

Fama and French (1993) proposed a parsimonious model that excluded any profitability measures, however, in 2015 they revised their work to include a profitability measure of earnings yield which gave their model a higher degree of accuracy (Fama & French, 2015).

In the South African context, Muller and Ward (2013), Strugnell et al. (2011), and Van Rensburg and Robertson (2003) all found that earnings yields, or price-to-earnings ratios, were significant predictors of returns to equity capital.

This was not surprising as Haugen and Baker (1996) found profitability measures to be strongly positively correlated to the cost of equity capital across both time-periods and different countries. Hence, the importance of earnings yield as a potential stylistic predictor of equity capital returns.

Given the strong academic support of the earnings yield measure, it was expected that this research paper would also find earnings yield to be a significant predictor of the cost of equity capital, with a strong positive correlation.

As can be seen, in Figure 7, in general, portfolios with higher earnings yields appeared to have outperformed those with lower earnings yields. However, unlike with the market-to-book style, the price relative, in green, also indicated that the outperformance of higher earnings yield firms had been relatively consistent and continued to be perpetuated.

When inferential statistics were employed, as seen in Table 40 and Table 41, a clear significant difference was found between higher earnings yield portfolios and lower earnings yield portfolios. Specifically, there was a significant effect on returns of the earnings yield, $F(4, 353) = 3.832$, $p=0.004$. There was a significant linear trend indicating that as earnings yield increased the returns also increased.

The Tukey post hoc analysis showed that there was a significant difference between the highest earnings yield ranked quintile, quintile 1, and the lowest earnings yield quintile, quintile 5, $p=0.002$. There was also a significant difference between the second highest ranked quintile, quintile 2, and quintile 5, $p=0.047$. The other quintiles did not display a statistically significant difference in their means.

These results supported the earlier work of Fama and French (2015), Haugen and Baker (1996), Muller and Ward (2013), Strugnell et al. (2011) and Van Rensburg and Robertson (2003). Therefore, the evidence, both from this research and previous research, resoundingly indicated that a positive correlation existed between earnings yield and the cost of equity capital.

6.4.4 Discussion of the Company Size Style

Internationally, numerous researchers found that a firm's size, measured in terms of its market capitalisation, could be used as an indicator of potential returns. They found that the firm's size was inversely related to potential returns to the equity capital (Asness & Frazzini, 2013; Fama & French, 1992, 2012, 2015; Fama & MacBeth, 1973; Hsu & Kalesnik, 2014).

In the South African financial markets, this effect was also found to be prevalent in numerous studies, across several industries and time periods, with smaller firms outperforming larger firms in terms of adjusted share returns (Hoffman, 2012; Strugnell et al., 2011; Van Rensburg & Robertson, 2003).

However, the research was not entirely unanimous with Jegadeesh and Titman (2001) observing that in earlier research periods of American data, 1965 to 1989, the size effect was present (Jegadeesh & Titman, 1993), but that it dissipated in their later research which examined data from 1990 to 1998 (Jegadeesh & Titman, 2001).

Similarly, although with more recent observations, Muller and Ward (2013) found that the South African financial market data showed a size effect was present amongst very small companies until December 2002, where after, the correlation ceased.

Harvey et al. (2014), in their meta-study, found that, on balance over all of the research they examined, a size effect did not appear to be present.

These contrasting findings made any prediction around whether a company size effect was present highly uncertain.

Graphically examining the empirical data, as seen in Figure 8, showed that the virtual portfolios performed very similarly with only a 2.8% difference between the best and worst performing portfolios. Furthermore, the price relative, in green, with a 0.0% hypothetical return showed that there was no sustained difference between portfolios formed from the largest and smallest of firms in the top 160 of the JSE' ALSI. Thus, this appeared to support the work of Harvey et al. (2014), Jegadeesh and Titman (2001), and Muller and Ward (2013). It should be noted that restricting the research to only shares in the top 160, based on market capitalisation, may have restricted access to extremely small firms, where an effect may have been observed. However, this restriction was in line with keeping the sample consistent.

Utilising inferential statistics, as seen in Table 44, revealed that a statistically significant relationship did not exist, ultimately concluding that there was no significant effect of the company size on the equity returns, $F(4, 290.791) = 0.144$, $p = 0.965$.

This finding was in support of Harvey et al. (2014), Jegadeesh and Titman (2001), and Muller and Ward (2013). Despite refuting the voluminous findings of Asness and Frazzini (2013), Fama and French (1992, 2012, 2015), Fama and MacBeth (1973), Hoffman (2012), Hsu and Kalesnik (2014), Strugnell et al. (2011) and Van Rensburg and Robertson (2003) this research found no correlation between firm size and equity cost.

6.4.5 Discussion of the Momentum Style

Asness et al. (2013), Carhart (1997) and Yu (2012) all found that, using American financial information, past share returns momentum was strongly correlated with abnormally high returns to equity on those shares, and thus, that momentum could be used to predict portfolio returns.

This finding was corroborated in other developed countries' financial markets by Hsu and Kalesnik (2014) who found that share return momentum was very significant in predicting future share returns. Harvey et al. (2014), found in their meta-study that, even across the vast range of studies conducted, share return momentum remained highly significant in determining likely returns on share portfolios.

Muller and Ward (2013) and Van Rensburg (2001) also examined share return momentum and empirically found that past share return momentum was also highly correlated to share returns in South Africa.

However, not all authors subscribed to the notion that historical share return momentum was correlated to future potential returns, and Marks (2013) dismissed momentum investing as being imprudent and irrational.

Even researchers who did find evidence of a momentum effect found that it was most significant when taking the previous 12 months' worth of returns, and that it often reversed after 12 months, with high share return momentum becoming correlated with abnormally low share returns (Jegadeesh & Titman, 2001; Moskowitz et al., 2012). Muller and Ward (2013), found that in the South African context similar patterns were present and that a 12 month momentum formation period, held for 3 months at a time, gave returns of 9% greater than the overall ALSI.

Given the existing body of research it appeared that most researchers found a positive correlation between returns and share return momentum, specifically 12 month momentum. Hence, it was expected that this research would also find such an effect present.

Graphically analysing the momentum effect, as seen in Figure 9, showed that portfolios with higher 12 month momentum far outperformed portfolios with lower momentum. This was most notably seen in the difference between the highest momentum portfolio and the lowest momentum portfolio, where a difference of 22.3% in annualised returns was observed. The price relative, in green, also showed that this difference had remained largely constant throughout the observed time period.

Thereafter, inferential statistics were used, as seen in Table 47 and Table 48, to test the significance, if any, of the positive relationship between momentum and the cost of equity. This showed that there was a significant effect on returns of the 12 month momentum, $F(4, 296.399) = 7.661, p=0.000$. There was a significant linear trend indicating that as momentum increased the returns also increased.

The Tukey post hoc analysis showed that there was a significant difference between the highest momentum ranked quintile, quintile 1, and quintiles 3, 4 and 5, $p = 0.029, p = 0.002$ and $p = 0.000$ respectively. There was also a significant

difference between the second highest ranked quintile, quintile 2, and quintile 5, $p = 0.004$. Finally, quintile 3 also exhibited a significant difference over quintile 5, $p = 0.042$. The other quintiles did not exhibit a statistically significant difference in their means.

These resounding findings clearly refuted Marks' (2013) claim that momentum had no effect on returns. Furthermore, the findings supported the burgeoning body of research of Asness et al. (2013), Carhart (1997), Harvey et al. (2014), Hsu and Kalesnik (2014), Muller and Ward (2013), Van Rensburg (2001) and Yu (2012) which had found a positive relationship between share return momentum and the cost of equity capital.

6.4.6 Discussion of the Optimising Returns Score Combined Models

For this section the null hypotheses stated that no time spent in any ORS quintile had any effect i.e. that each of the quintile return constants ($R_{Q\dots}$) was equal to zero, hence, rendering that quintile's impact statistically insignificant. The alternative hypotheses stated that time spent in at least one of the ORS quintiles had an effect on the expected returns of a specific firm's equity. This ultimately led to the following hypotheses.

For non-resource shares

$$H3a_0: R_{Q1} = R_{Q2} = R_{Q3} = R_{Q4} = R_{Q5} = 0$$

$$H3a_A: \text{At least one } R_Q \text{ is not zero}$$

And for resource shares

$$H3b_0: R_{Q1} = R_{Q2} = R_{Q3} = R_{Q4} = R_{Q5} = 0$$

$$H3b_A: \text{At least one } R_Q \text{ is not zero}$$

In Hsu and Kalesnik's (2014) research they identified various market factors as being significant across numerous research studies. Fama and French (1992, 1993, 2012, 2015) had found numerous multi-factor models, over many years, that were capable of improving the accuracy of projections of the cost of equity. Montier (2007) also found a selection of variables, which captured a firm's fundamentals, which had a far greater correlation with returns than the modest beta.

Muller and Ward (2013) showed that similar multi-factor models could also improve share return projections in the South African context. Thus, the underlying theoretical principle that multi-style models could predict equity returns was well established, and meant that the ORS combined models could potentially have produced significant results.

However, a significant difference in the ORS combined models came about due to the additional layer of aggregation through which the initial individual ORS was calculated with an optimised constituent style rating, before being ranked into market relative quintiles. Furthermore, the subsequent measuring of the historical time spent in each of those quintiles and regressing that back to the eventual returns, resulted in a combined method and model that, to the knowledge of the author of this research paper, was a first.

Due to this differing, more indirect, technique the eventual outcome of the statistical analysis could not be predicted, despite the multitude of research supporting the philosophy of a multi-factor model (Fama & French, 1992, 1993, 2012, 2015; Hsu & Kalesnik, 2014; Montier, 2007; Muller & Ward, 2013).

6.4.6.1 Discussion of Non-Resources ORS

Post the optimised weighting of the ORS portfolios, as seen in Table 49, the weights of the styles within the portfolios were assigned with momentum 12 months 71.43%, earnings yield 28.57%, market-to-book 0% and company size 0%.

Market-to-book and company size being left out of the weighted portfolios supported the findings in Table 37 and Table 44, where they were found not to be significant predictors of the cost of equity.

Given these optimised weightings, Figure 11, was generated showing that the quintiles based upon the ORS performed in accordance with the ORS ranking appearing in descending order from quintile 1 through quintile 5. This suggested that the null hypothesis for non-resource shares, $H3a_0$, would likely be rejected.

The next step in the evaluation was to test the ORS portfolios for statistical differences, as seen in Table 52 and Table 53, to test the significance, if any, of the positive relationship between the ORS ranked portfolios and the cost of equity. This showed that there was a significant effect on returns of the ORS ranking, $F(4, 595)$

= 4.948, $p = 0.001$. There was a significant linear trend indicating that as ORS ranking increased the returns also increased.

The Tukey post hoc analysis showed that there was a significant difference between the highest optimised returns score ranked quintile, quintile 1, and quintile 5, $p = 0.000$. The other quintiles did not exhibit a statistically significant difference in their means.

Thereafter, further inferential statistics were generated. The initial observation, drawn from Table 54, was that the gradients for quintiles 4 and 5 were negative, which was expected given that those quintiles were the lowest ranked of the ORS portfolios.

As seen in Table 55, the third model had the greatest R^2 adjusted value, signalling that it would be the best at explaining variation in the total population. This model had quintile 5, 1 and 4 as its contributing independent variables. It was also the last model where the addition of new measures of time spent in a quintile, specifically quintile 4, had a significant effect on the explanatory power, $p = 0.003$.

Thereafter, the multiple regression was performed, as seen in Table 56. The first point to note was that time spent in quintile 1, was not significant with $p = 0.591$. Thus, time spent in quintile 1 needed to be removed from the model and the regression needed to be rerun.

These rerun results were seen in Table 58. The first noteworthy point was that all of the variables measuring the time spent in specific quintiles had VIF values below 10, and tolerance values greater than 0.2, which were the hurdle criteria laid out by Field (2013) to ensure that no distorting multicollinearity was present in the results.

This meant that the results from Table 58 could be interpreted to establish if the null hypothesis could be rejected or not. The constant, time spent in quintile 5 and time spent in quintile 4 were all found to be significant, with $p = 0.000$, $p = 0.000$ and $p = 0.000$ respectively. Thus, the null hypothesis, H_{3a_0} , was rejected, in support of the assertions of previous researchers such as Fama and French (1992, 1993, 2012, 2015), Hsu and Kalesnik (2014), Montier (2007) and Muller and Ward (2013) that multi-factor models could be significant predictors of the cost of equity capital.

Additionally, the outputs from Table 58 led to the formation of the eventual ORS combined model for non-resources, as seen below in Equation 9. This had

explanatory power of $R^2 = 0.365$, as seen in Table 57 thus explaining 36.5% of the variation in the returns of non-resource shares. The detection of such a large effect was in line with the discussion in section 4.7.4.2, where it was highlighted that there were sufficient observations in the sample to allow for detection of medium and large effects.

Equation 9: ORS Combined Model for non-resources

$$E(\tilde{R}_i) = 0.379 - 0.428(\text{Time Spent in ORS Quintile 4}) - 0.427(\text{Time Spent in ORS Quintile 5})$$

where,

$E(\tilde{R}_i)$ is the expected return for share i ;

Time Spent in ORS Quintile 4 is the time spent in ORS quintile 4, expressed as a percentage of the shares total period of existence;

Time Spent in ORS Quintile 5 is the time spent in ORS quintile 5, expressed as a percentage of the shares total period of existence.

6.4.6.2 Discussion of Resources ORS

Post the optimised weighting of the ORS portfolios, as seen in Table 59, the weights of the styles within the portfolios were assigned with momentum 12 months 23.26%, earnings yield 32.56%, market-to-book 23.26% and company size 20.93%.

Given these optimised weightings, Figure 13, was generated showing that the quintiles based upon the ORS performed in accordance with the ORS ranking with the quintiles performing, in descending order from quintile 1 through quintile 5. This suggested that the null hypothesis for resource shares would likely be rejected.

The next step in the evaluation was to test the ORS portfolios for statistical differences, as seen in Table 62 and Table 63, to test the significance, if any, of the positive relationship between the ORS ranked portfolios and the cost of equity. This showed that there was a significant effect on returns of the optimised returns score for resources, $F(4, 294.245) = 4.576$, $p=0.001$. There was a significant linear trend indicating that as optimised return scores increased, the returns also increased.

The Tukey post hoc analysis showed that there was a significant difference between the highest optimised returns score ranked quintile, quintile 1, and quintile 5, $p = 0.003$. The other quintiles did not exhibit a statistically significant difference in their means.

However, as seen in Table 65, none of the models made a significant change as time spent in the various ORS quintiles was added into the model with $p = 0.319$, $p = 0.807$, $p = 0.955$ and $p = 0.513$.

Given that none of these models was significant the null hypothesis, $H3b_0$ for the resource ORS could not be rejected. This may have been as a result of the low number of observations in the sample, as discussed in section 4.7.4.2, where it was found that the ORS combined model for resources would struggle to be able to detect any effects due to a small sample size. This was further supported by the findings in Table 62 and Table 63, where a significant relationship was found between the ORS quintile rankings and total cost of equity.

6.5 Summary of the Discussion of the Results

Based on the evidence observed and the subsequent discussion in this section, it was observed that the original CAPM, in any guise, appeared to be a poor predictor of the cost of equity. However, it should be noted that the original CAPM with a conventional 24 month look-back period was not statistically rejected, although, the indications that a type II error had occurred, made it too seem like an unsuitable equity pricing model.

The Black's CAPM analyses and discussion appeared to reveal an even worse predictive ability with all of the variations tested being soundly rejected. Directly refuting the research of Strydom and Charteris (2013) through also testing over the same time periods.

Finally, the analysis focussed on the relationship between styles and market relative returns. The findings here were varied, with sector styles and market-to-book styles visually appearing to hold a relation to share price returns, however, when examined statistically the differences were found to be non-significant. Market-to-book was particularly interesting as it appeared to present evidence that whilst the

style had worked in earlier years; it had ceased to have any predictive capability since approximately 2004.

Company size, despite voluminous research supporting its presence, both visually and statistically was found to hold no relation to the cost of equity.

The only styles that held both a visual and statistically significant relationship to the returns on equity capital were the earnings yield style and share returns momentum style. Given that momentum had the highest level of significance based upon the outputs from the inferential statistical tests it was used as the anchor style in the weighting of the ORS portfolios that were formed to test the ORS combined models.

The tests of the ORS combined models revealed that while an alternative model could be proposed for the prediction of the cost of equity capital for non-resource shares, a statistically significant model could not be generated for resource equity costing, possibly due to its small sample size.

The generated costing model for non-resources was able to explain 36.5% of the variation in the cost of equity, and is shown below.

Equation 10: ORS Combined Model for non-resources

$$E(\tilde{R}_i) = 0.379 - 0.428(\text{Time Spent in ORS Quintile 4}) \\ - 0.427(\text{Time Spent in ORS Quintile 5})$$

6.6 Limitations Imposed Upon Results

A factor that needs to be considered is that the CAPM attempts to predict a future cost of equity capital, however, when exactly this predicted cost is expected to realise is not clearly defined. This study looked at two time horizons, namely 24 months and five years, but it may be possible that over a longer time period, when reversion to the mean has fully been factored in, and cyclical market fluctuations have been largely smoothed out, that a different set results may be observed.

The comparatively small sample size of the resource shares may have played a contributing role in being unable to form a predictive multiple regression model for

the ORS combined model for resources, despite the presence of a statistically significant difference.

Another limitation is the limitation on the number of styles it is practicable to test. Harvey et al. (2014) conducted a meta-study of all of the characteristics, known as styles, which had been mooted as potential predictors of returns, or viewed differently as the potential cost of equity capital for an asset. Their research, which utilised well respected journals and working papers, identified 316 styles that had been researched. Additionally, they also noted a significant proliferation of research into styles during the later periods of their study, with 59 new styles being proposed between 2010 and 2012 (Harvey et al., 2014). Thus, it is possible that one of the untested styles, or a combination of these, may be superior predictors of the cost of equity capital.

Another potential limitation that was introduced is that in the weighting of the ORS portfolios the weights of each style were tested in increments of ten percent, but this did not preclude the possibility that a finer level of granularity employed in the weighting of the styles may have rendered improved optimisation of the first quintile's returns.

Muller and Ward (2013), also cautioned that any styles with a correlation to returns on capital were likely to be short-lived in nature. Meanwhile, Siegel (2014) dismissed the use of styles as wholly frivolous, due to the very fact that investing based on styles projected cost of capital would influence the very outcomes that the investors wished to capitalise upon. Hence, there was a risk that any identified styles may cease to predict abnormal returns before they could be utilised for consistent prediction.

Chapter 7 Conclusion

7.1 Principal Findings

The purpose of this research paper was two-fold. Firstly to test whether the CAPM, and any of its variations were applicable to the South African financial markets and then, if required, to find an alternative model that could possibly provide an improved method for projecting the appropriate cost of equity capital.

On the first of the purposes, the original CAPM was tested in numerous guises, through varying the look-back periods employed for the beta calculations as well as modifying the beta through the use of the Dimson' beta calculation method- also with varied look-back periods employed. In only one of the four hypotheses tested was the use of the original CAPM not statistically rejected. This sole potential CAPM candidate was the original CAPM with a conventional 24 month look-back beta. However, upon examination of the descriptive, graphical analysis as well as the individual time series analysis, the probability that a type II error had occurred, failing to reject the CAPM when it should have been rejected, appeared disconcertingly large. Thus, the position of this paper is that even the employment of this variation of the CAPM would be strongly discouraged.

The subsequent set of tests aimed at testing the applicability of the CAPM, looked at a variation of the CAPM, known as the Black's CAPM. This variation of the CAPM had recently been used by Strydom and Charteris (2013) where they found the Black's CAPM to be applicable to the South African financial markets. Again, the Black's CAPM was tested using a variety of configurations that accounted for differing beta look-back periods and trade illiquidity through the use of the Dimson' beta. All of these tests statistically rejected the use of the Black's CAPM, and as such, the position of this paper is that the Black's CAPM should be discarded as a tool for the estimation of equity capital costing in the South African financial markets.

To consolidate the findings surrounding the CAPM, the underlying precept that higher risk, measured through beta, led to higher returns was statistically dispelled. The actual results of these tests found that a negative relationship, and not the CAPM claimed positive relationship, existed between beta and returns, thus that the CAPM employed a complete inversion of the empirically observed relationship, which supported the findings of Pettengill et al. (1995), Frazzini and Pedersen

(2014), Lazar and Yaseer (2010) and Ward and Muller (2012, 2015b). Thus, that the CAPM is fundamentally flawed and should be cast aside as an equity costing tool, despite its widespread usage in academia and business.

An improved alternative to the CAPM was generated for the pricing of non-resource shares, which could explain 36.5% of the variation in the cost of equity. However, a statistically significant model was not able to be produced for the cost of equity for resource shares, possibly due to the far smaller sample size. The eventual model found for costing the equity capital of non-resource shares is as displayed below.

Equation 11: ORS Combined Model for non-resources

$$E(\tilde{R}_i) = 0.379 - 0.428(\text{Time Spent in ORS Quintile 4}) - 0.427(\text{Time Spent in ORS Quintile 5})$$

7.2 Implications for Management

The implication for management is significant and should be addressed from a dual perspective. Firstly, if, as surmised by Graham and Harvey (2001), the practice of utilising the CAPM in the business arena is partially due to the widespread teaching of the said CAPM in business schools, then any alteration to the paradigm within business would need to begin in the business schools.

As such, the recommendation would be to abandon the teaching of the CAPM, and replace it with teaching based upon the empirical evidence, rather than theoretical suppositions. Whilst the position of this paper is to remain cognisant of the fact that empirical trends may change during the course of time, and that the CAPM may experience some future relevance, this should only be taught in support of empirical data-driven research to ensure that future generations of business men and women apply empirically based decision-making.

Secondly, given that Correia and Cramer (2008), found the usage of the CAPM in South African industry to be pervasive, companies should view the opportunity to move away from the flawed CAPM costing model, to the ORS combined model, at least for non-resources, as a potential competitive advantage. In any given industry

a firm that can consistently make superior business decisions should attain preferable long-term performance. As with any competitive advantage, firms should look to embrace it of their own accord, although demonstration of superior performance may be required given the embedded nature of the use of the CAPM.

To this end, early-adopting firms may wish to trial the use of the ORS combined model for non-resources, potentially in parallel to their existing costing models, but retrospective demonstration of future correlation with results may be required for the ardent CAPM devotees. However, given the inherent flaws discovered in the CAPM and the suggested out-performance of the ORS combined model for non-resources, early adoption would be recommended.

One final caveat, worth acknowledging is that the ORS combined model for non-resources does not have the simplistic parsimonious elegance of the CAPM. The ORS combined model for non-resources would take far longer to compute and require access to more historical data. However, this needs to be weighed against the potential gains, especially given the failings of the CAPM, and this paper's position is that this would be a worthwhile sacrifice of parsimoniousness. The fact that an OSR combined model was not able to be generated for resource shares too, whilst being a drawback is not crippling as the majority of the shares on the JSE ALSI are non-resource shares in any event.

7.3 Limitations of the Research

From a statistical perspective, there were certain limitations imposed. The inability to remove multicollinearity fortunately proved not to be a concern for this research paper. However, the incapability to confidently detect any size effects of the ORS combined model for resources, due to the size of the sample, may have prevented the formation of such a model. The size of the sample could well have been increased through the use of more frequent return sampling, rather than just the ending return, although this would have exposed the model to more volatility. As more financial data gets collected, in future the frequency could be increased, without introducing excessive volatility.

Survivorship bias was largely eliminated through the inclusion of delisted shares in all of the calculated portfolios, apart from the shares used for the calculation of the

minimum variance zero-beta portfolios in the Black's CAPM analysis. This survivorship bias would only have applied to those shares that ceased to exist during the course of each individual time period, so would be extremely small, but bears mentioning nonetheless. Another area of potential survivorship bias was that of the final ORS combined models calculation where only existing shares' returns were included in the multiple regression. This, was however, deemed acceptable due to the fact that only existing firms would need to calculate costs of equity.

There were also certain non-statistical limitations imposed by using the selected sample. Perhaps most obviously, given the South African focus of this research, conclusions about international financial markets and the associated cost of equity capital should be cautiously drawn, as each international exchange has marginally different regulations which may impact results. The differing prevailing inflation rates would also greatly impact the real returns achieved, however, this would have largely been offset through the use of market relative returns in the statistical analyses. The South African focus also greatly reduced the number of prior research papers available for review and comparison, as comparatively few studies had been performed on South African financial data.

Any unlisted firms were also not accounted for, and non-profit organisations were also not represented. Amongst the potential alternative independent variables, the only distinction between industries was between resource shares and non-resource shares; however, this did not exclude the possibility that within specific industries, the independent variables may have had entirely different impacts on the dependent variable.

There were also numerous other potential independent variables, 316 of which were identified by Harvey et al. (2014), that may have been investigated but were excluded from this research in the interests of scale, and limited prior research recommending them as likely predictors of returns.

It should also be noted that the results may well not hold for equity traded prior to the date range under examination, nor into the future. In future there may be external occurrences, such as legislative changes that affect the results. Although the use of market relative returns on equity in this study should have minimised this risk, certain external events may affect the future cost of equity capital in such a way that other forms of financing may become preferable to the equity market as a whole.

The omission of transaction costs, while applied to all portfolios that were compared to reduce the impact, may have impacted certain portfolios more than others depending on the number of shares that were virtually traded into or out of a portfolio which may have skewed some of the results (Mutooni & Muller, 2007). Furthermore, transaction costs would oftentimes not have been a percentage of the total trade value, and could have been an absolute amount. Thus, larger value portfolios would have had relatively lower percentage-based transaction costs, whilst the issuance or trading of smaller values of equity may have been relatively more expensive due to the higher proportion of transaction costs that would have raised the required returns on equity to offset this.

The differences between bid and ask prices were also not taken into account, although the impact of this limitation would be expected to be marginal due to the highly liquid equity that was used in this research, as seen in the similar standard and Dimson' beta results.

The share prices used were only the end of trade prices so intraday fluctuations were ignored, which may have resulted in the research missing potential effects (Kappou et al., 2008). Additionally, only rebalancing portfolios at the start of each quarter may have meant that potential style effects were underestimated due to a slowness to respond based on the timing of rebalancing selected for this research.

The research also did not delve into the underlying reasons that the independent variables exhibited the correlations with the returns. Thus, the research only indicated whether a relationship existed and what the size of that relationship was, not the cause. Related to this, the research addressed historical relationships, but as with any potential arbitrage opportunities the market has historically responded to nullify those inefficiencies, particularly in the highly computerised era (Chaboud, Chiquoine, Hjalmarsson & Vega, 2014).

Finally, and potentially most pertinently, given the South African government's focus on developing small to medium sized enterprises (South African Presidency, 2011), these small to medium sized enterprises were excluded from the analysis as they had insufficient market capitalisation to be included in the top 160 shares.

7.4 Suggestions for Future Research

A generic future area for research could be related to the fact that all of the virtual portfolios created in this research, whether researching the relationship underlying the CAPM or the alternative predictive styles, were rebalanced at the end of every quarter. This rebalancing frequency could be suboptimal, and hence, further research to find a more optimal frequency could be highly beneficial, although cognisance must be kept surrounding the impact that this would have on transaction costs.

Specifically related to the CAPM, research could be conducted into when, if ever, the CAPM prediction is realised, as the CAPM itself does not stipulate the appropriate time horizon to be tested over. This paper tested the CAPM over a 24 month and 60 month horizon, but there may be more appropriate alternative time periods.

Also related to potential further research into the CAPM, it must be noted that not all of the individual time periods under evaluation found against the use of the CAPM, as seen in Table 13 and Table 27. Further research could delve into the underlying market conditions that prevailed during those time periods where the CAPM held to see if any trends could be observed.

Related to this understanding of underlying conditions, this paper only tested for the presence of underlying relationships, but not the reasons for the existence of these relationships. Researchers, such as Baker et al. (2011), have conducted some research into understanding why the risk return relationship potentially did not hold, but there is still a large scope for understanding the reasoning behind the observed relationships.

In the realm of style correlations with returns, there remains a myriad of different styles that were not tested as part of this research. Some of these styles, or a combination thereof, may well be able to raise the R^2 from its current value of 0.365 for the non-resources ORS combined model, or even find a statistically significant predictive model for resource shares.

Additionally, in sections 5.4.4.2 through 5.4.4.5 the styles tested were not tested in relation to their effect on different sectors of the financial markets. As seen in section 5.4.4.1, there were significant differences between sectors, and potentially on the predictive power of styles within sectors too, and more research into this area could be very revealing.

Looking at the ORS computation, all of the time periods during which a share fell into a specific quintile were equally weighted. However, there may be scope to improve the returns and predictive capability through either increasing the weight of earlier periods classification due to the power of compounded returns, or perhaps through weighting later periods more highly due to their closer relation in time with the eventual returns. In either scenario, further research could improve the predictive power of the model. There is also a clear need to increase the number of sample points in the ORS combined model for resources, and future research could focus on reliable manners of increasing the sample size without exposing the model to undue volatility.

Finally, dependent upon the adoption of the ORS combined models adoption, a comparative study could be conducted in future to determine whether institutions employing the ORS combined model engaged in more profitable projects and acquisitions than those who utilised the CAPM.

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Appendices

Appendix 1 – Turnitin Report

Not required for electronic submission.

Appendix 2 – Graphical Analysis Original CAPM, 24 month beta

Figure 14: Original CAPM vs Actual Returns, 24 month beta, 31 Dec 1986 - 31 Dec 1988

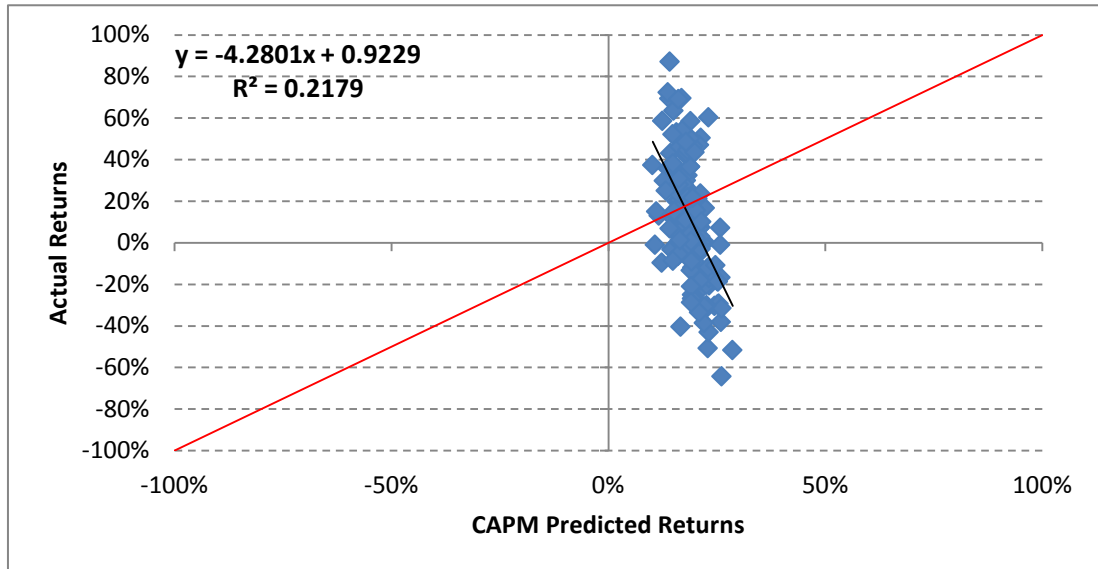


Figure 15: Original CAPM vs Actual Returns, 24 month beta, 31 Dec 1988 - 31 Dec 1990

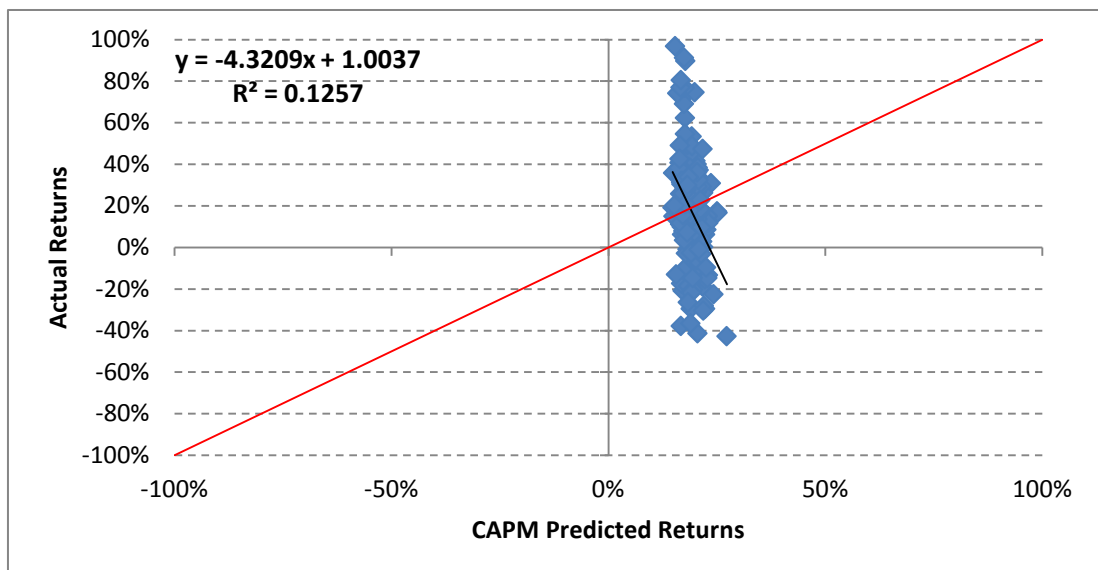


Figure 16: Original CAPM vs Actual Returns, 24 month beta, 31 Dec 1990 - 31 Dec 1992

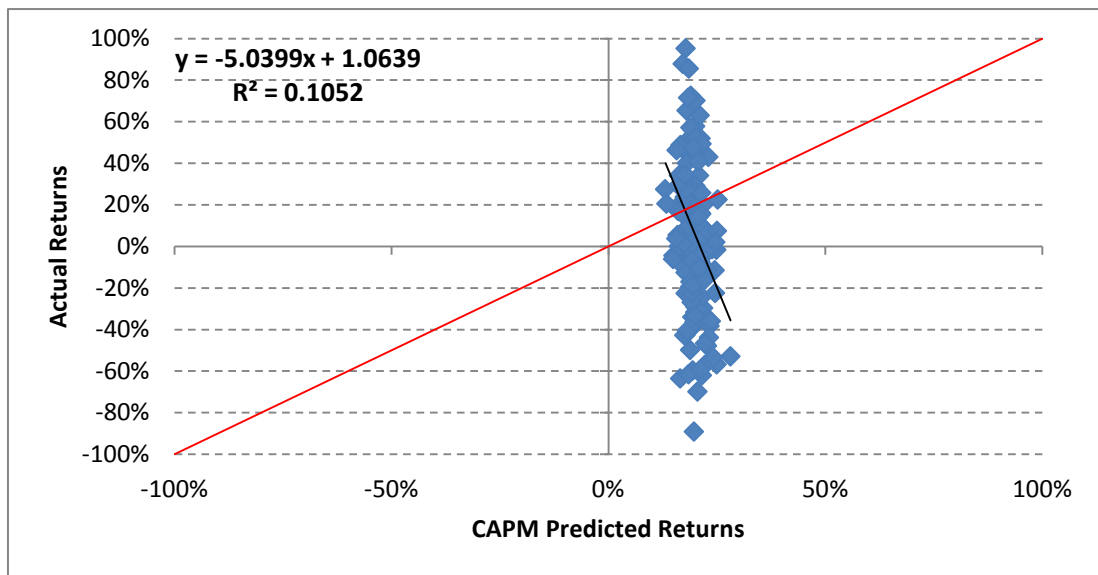


Figure 17: Original CAPM vs Actual Returns, 24 month beta, 31 Dec 1992 - 31 Dec 1994

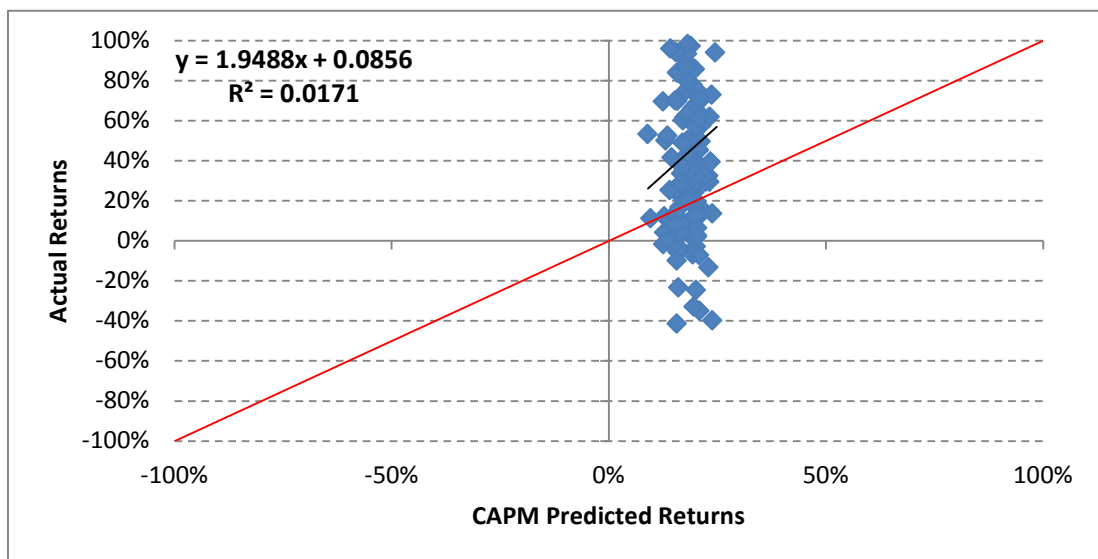


Figure 18: Original CAPM vs Actual Returns, 24 month beta, 31 Dec 1994 - 31 Dec 1996

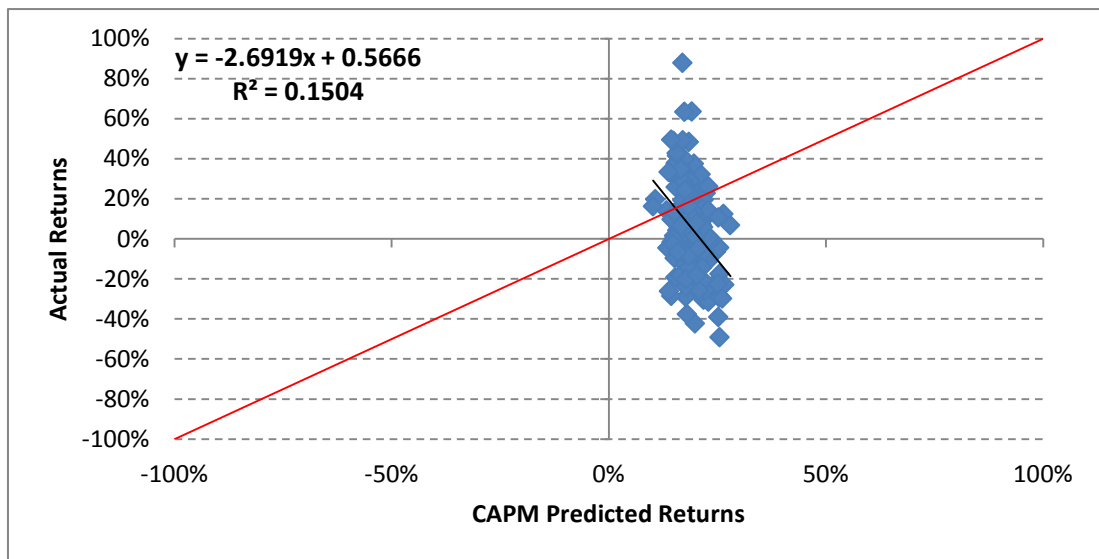


Figure 19: Original CAPM vs Actual Returns, 24 month beta, 31 Dec 1996 - 31 Dec 1998

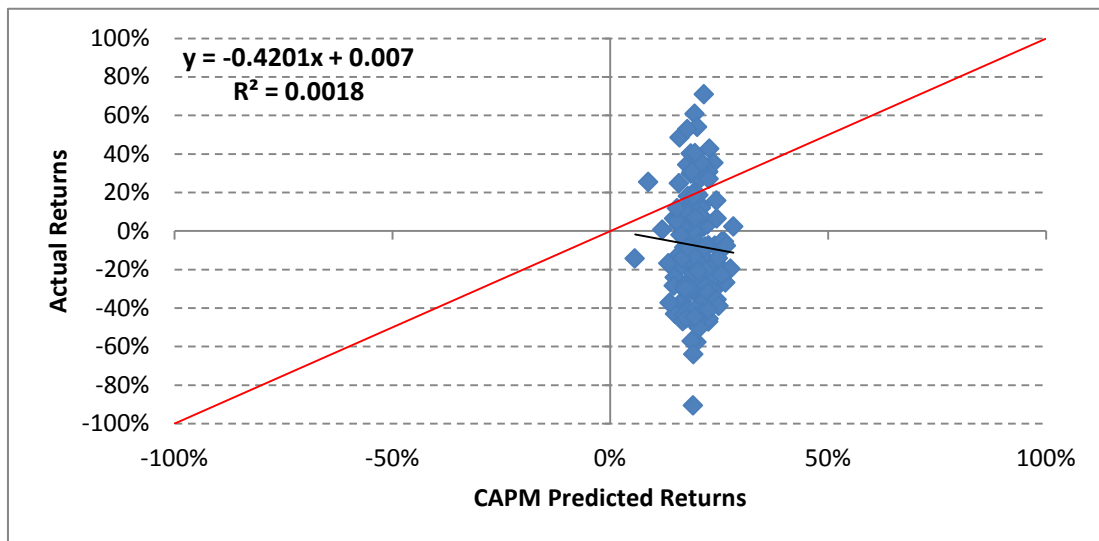


Figure 20: Original CAPM vs Actual Returns, 24 month beta, 31 Dec 1998 - 31 Dec 2000

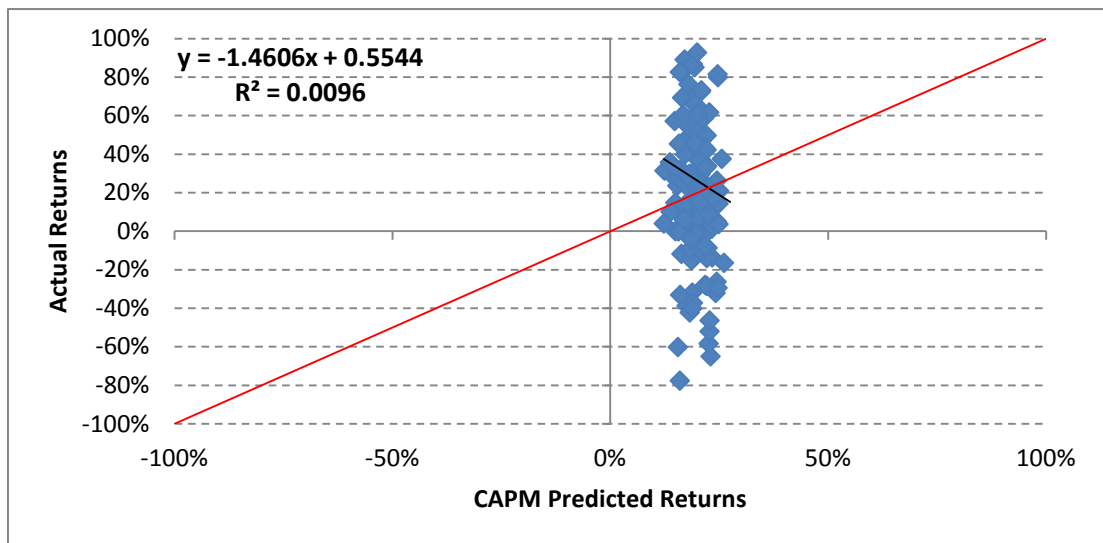


Figure 21: Original CAPM vs Actual Returns, 24 month beta, 31 Dec 2000 - 31 Dec 2002

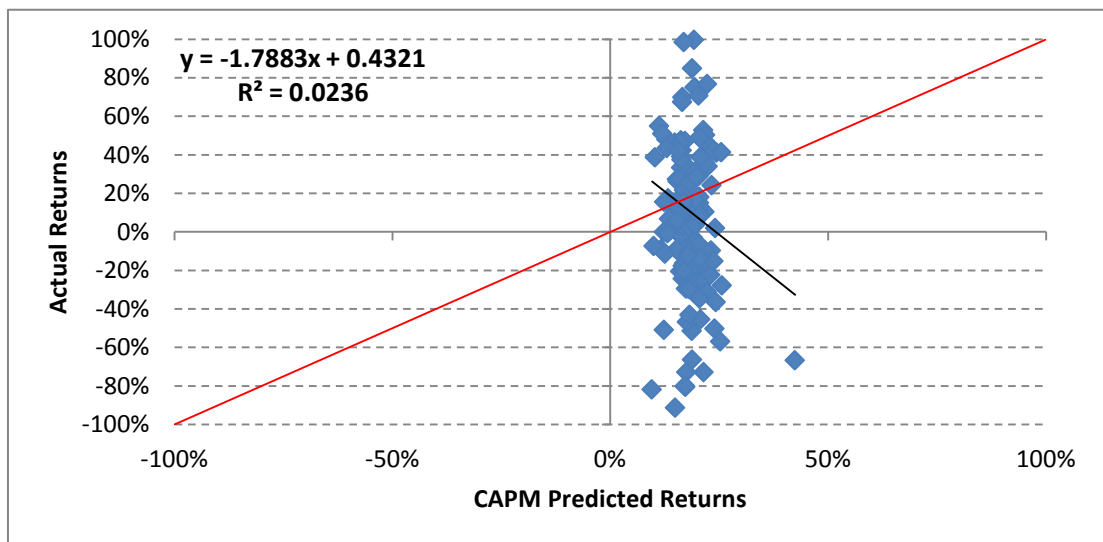


Figure 22: Original CAPM vs Actual Returns, 24 month beta, 31 Dec 2002 - 31 Dec 2004

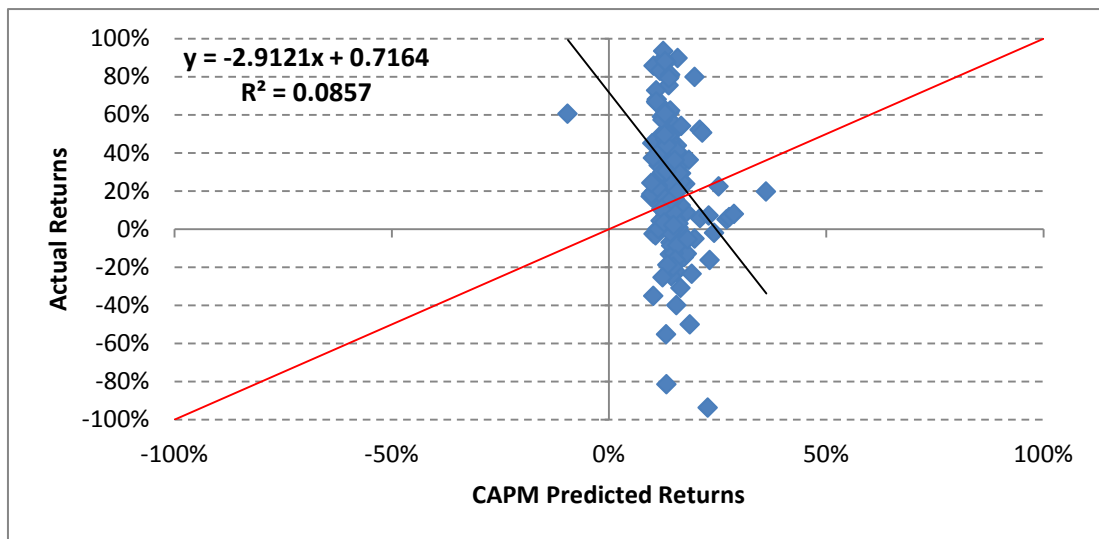


Figure 23: Original CAPM vs Actual Returns, 24 month beta, 31 Dec 2004 - 31 Dec 2006

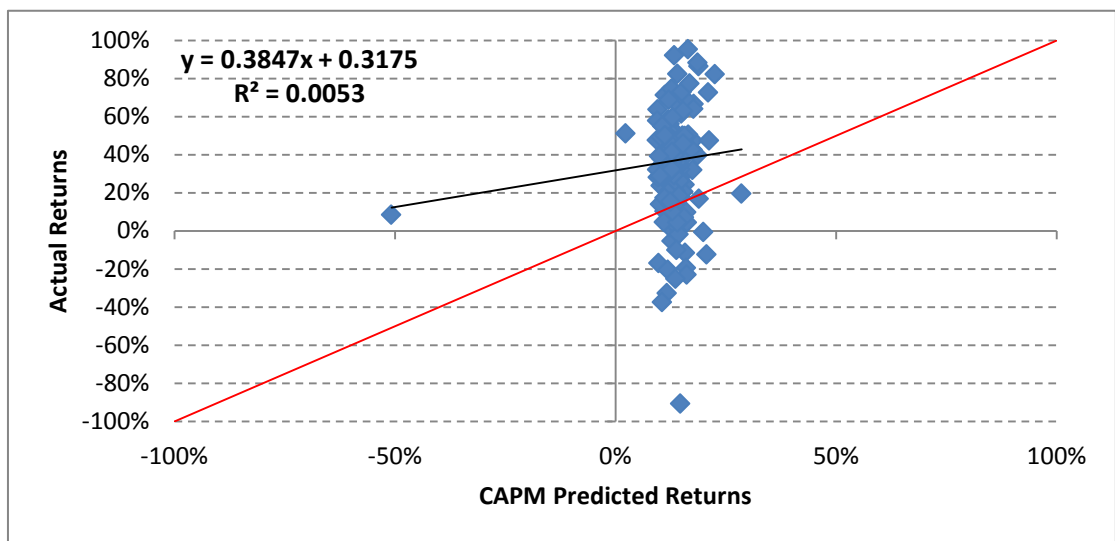


Figure 24: Original CAPM vs Actual Returns, 24 month beta, 31 Dec 2006 - 31 Dec 2008

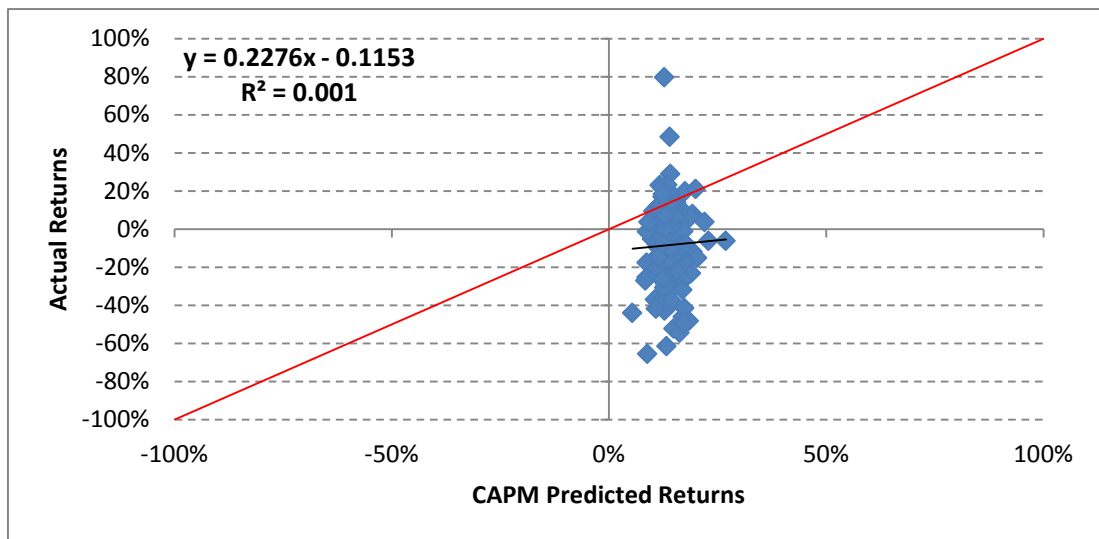


Figure 25: Original CAPM vs Actual Returns, 24 month beta, 31 Dec 2008 - 31 Dec 2010

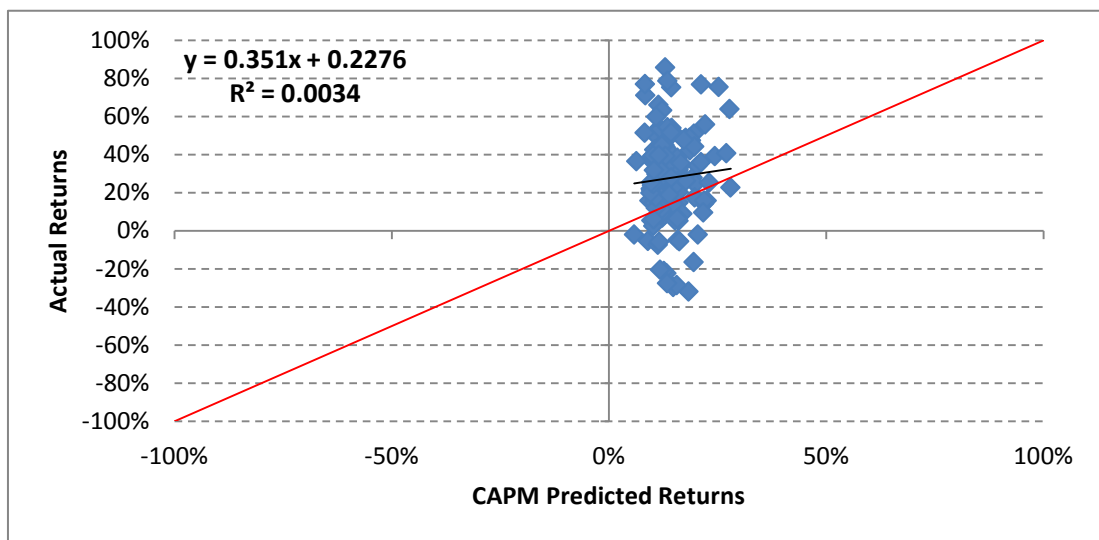


Figure 26: Original CAPM vs Actual Returns, 24 month beta, 31 Dec 2010 - 31 Dec 2012

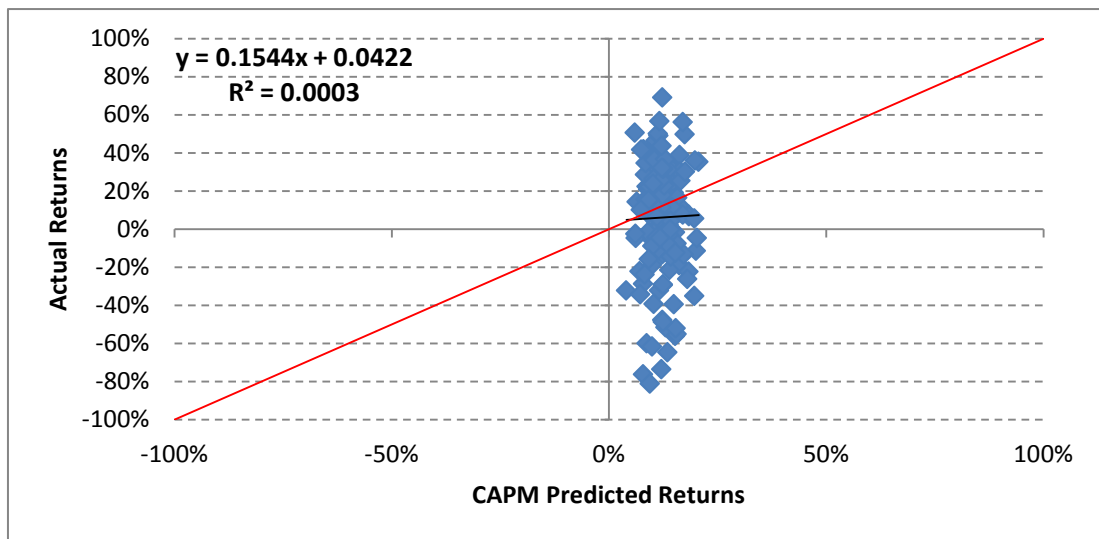
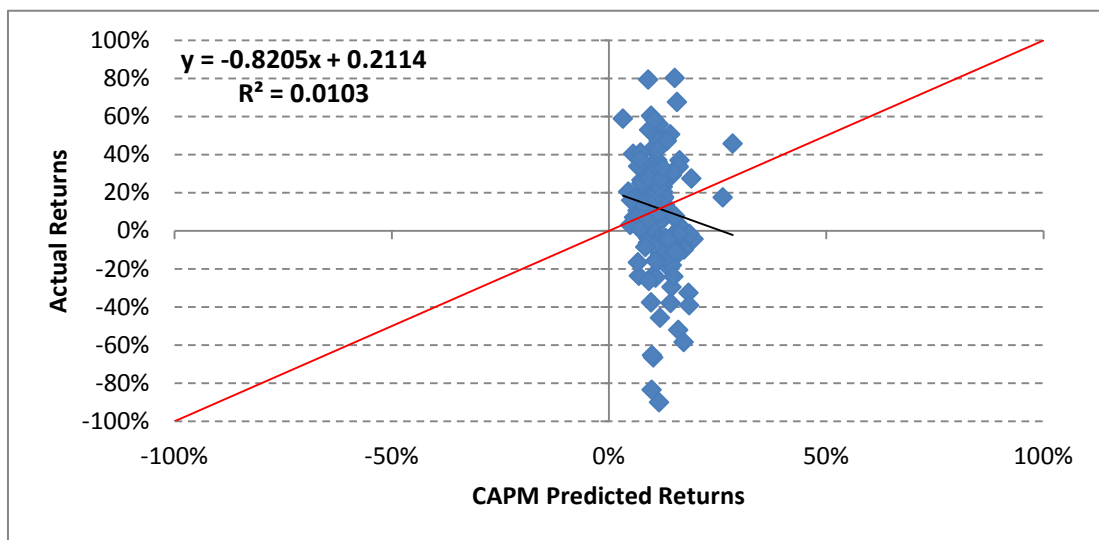


Figure 27: Original CAPM vs Actual Returns, 24 month beta, 31 Dec 2012 - 31 Dec 2014



Appendix 3 – Graphical Analysis Original CAPM, 60 month beta

Figure 28: Original CAPM vs Actual Returns, 60 month beta, 31 Dec 1989 - 31 Dec 1994

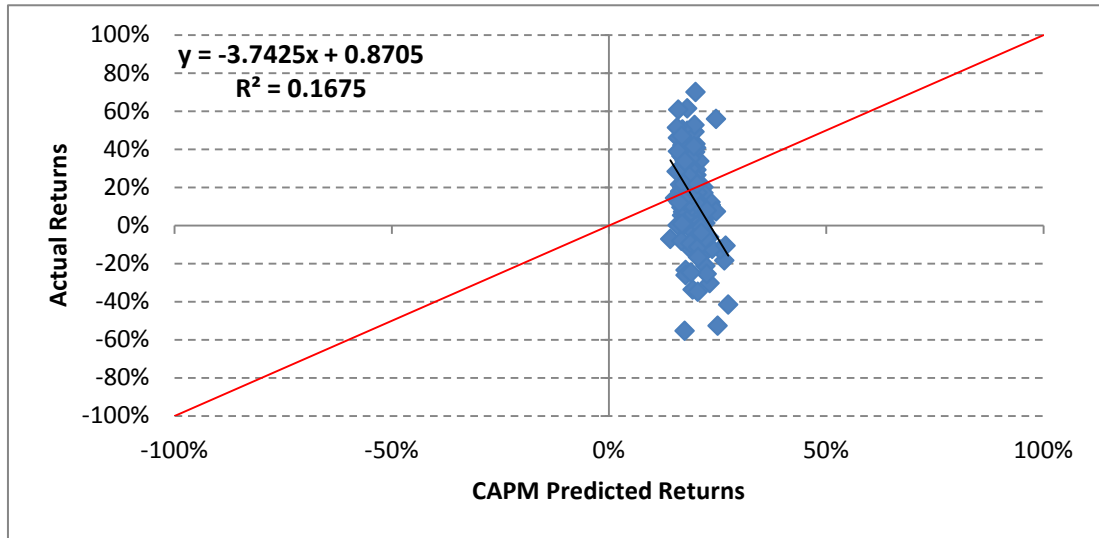


Figure 29: Original CAPM vs Actual Returns, 60 month beta, 31 Dec 1994 - 31 Dec 1999

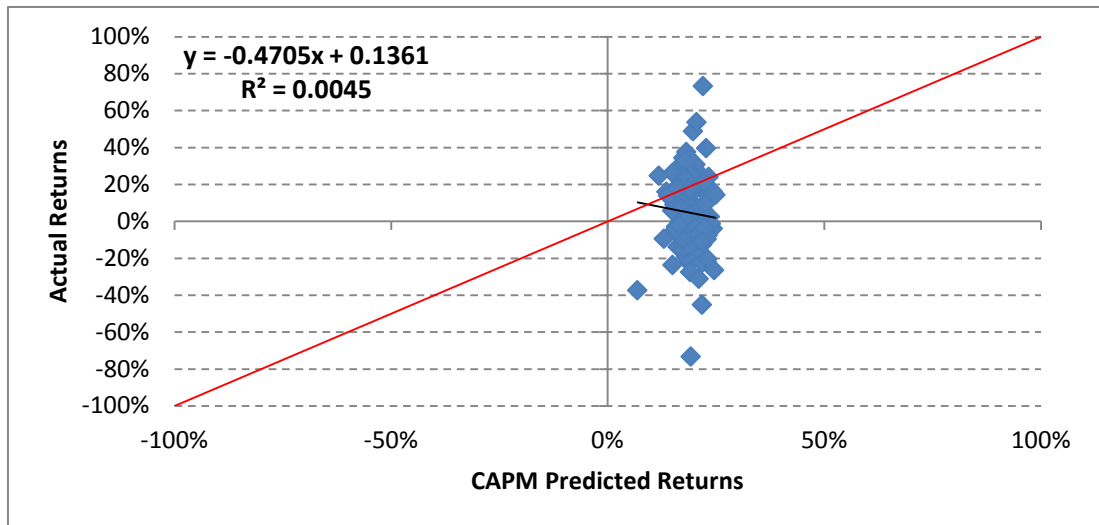


Figure 30: Original CAPM vs Actual Returns, 60 month beta, 31 Dec 1999 - 31 Dec 2004

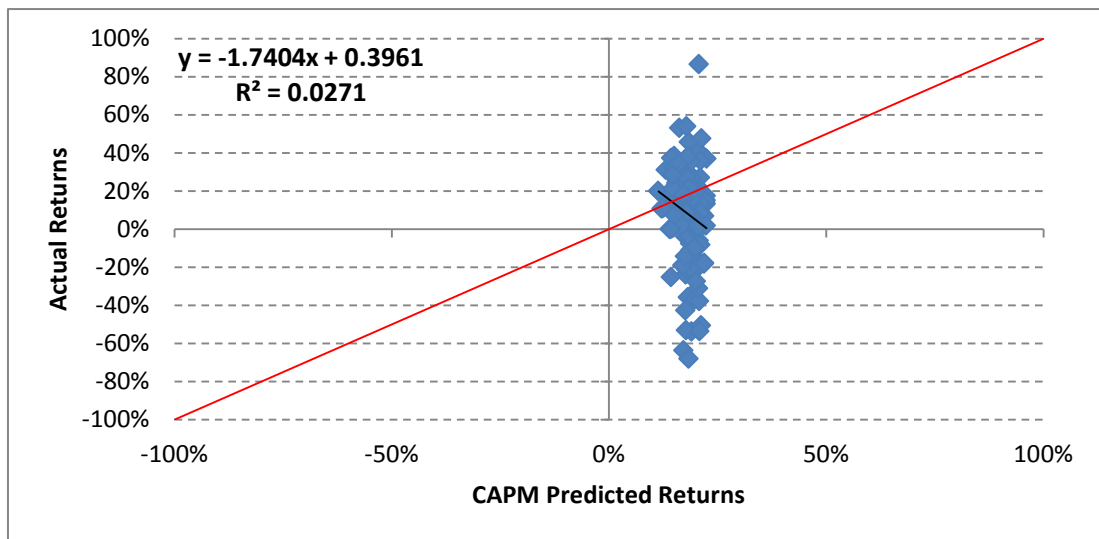


Figure 31: Original CAPM vs Actual Returns, 60 month beta, 31 Dec 2004 - 31 Dec 2009

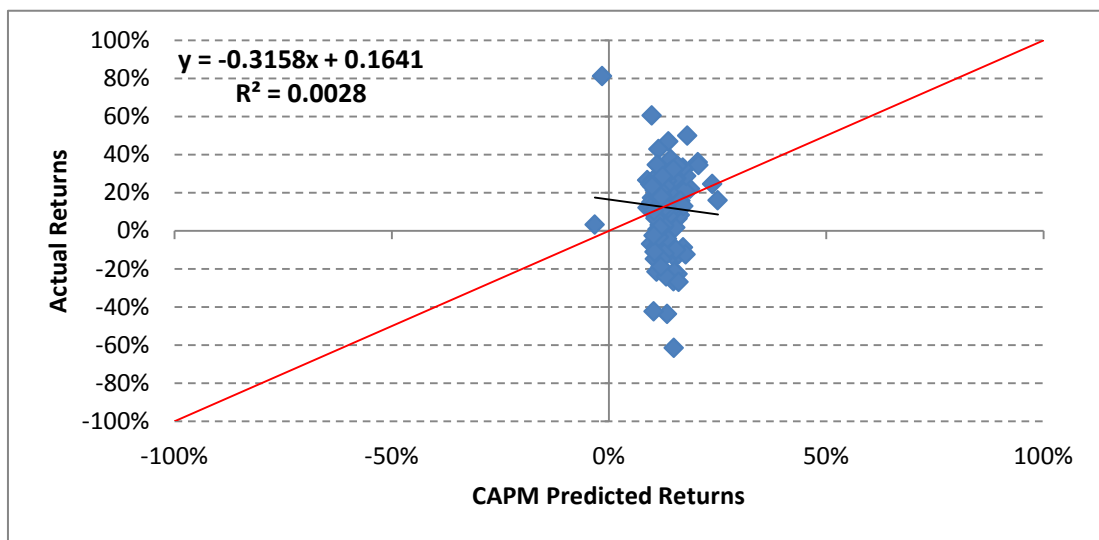
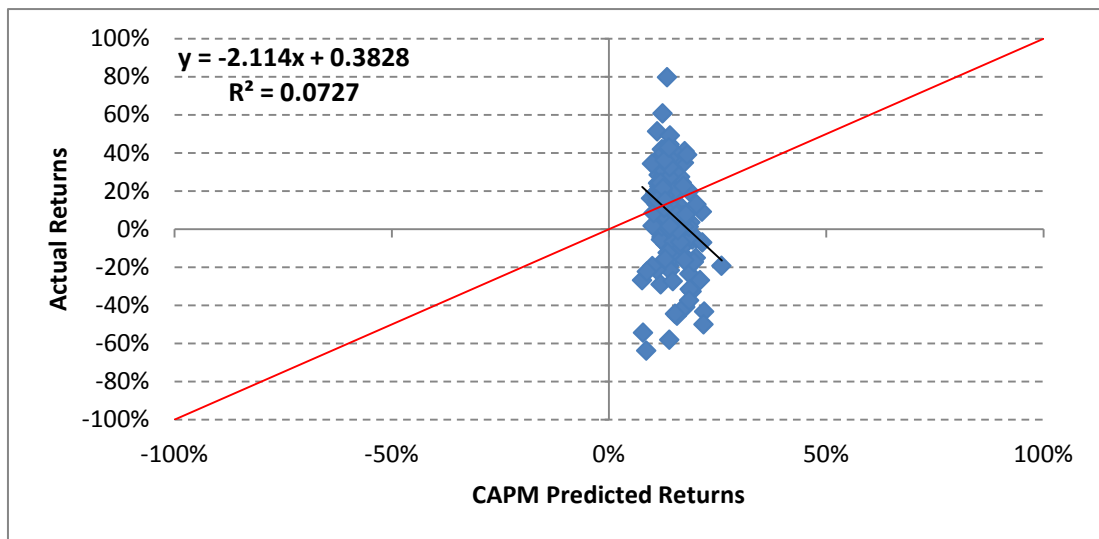


Figure 32: Original CAPM vs Actual Returns, 60 month beta, 31 Dec 2009 - 31 Dec 2014



Appendix 4 – Graphical Analysis Original CAPM, Dimson 24 month beta

Figure 33: Original CAPM vs Actual Returns, Dimson 24 month beta, 31 Dec 1986 - 31 Dec 1988

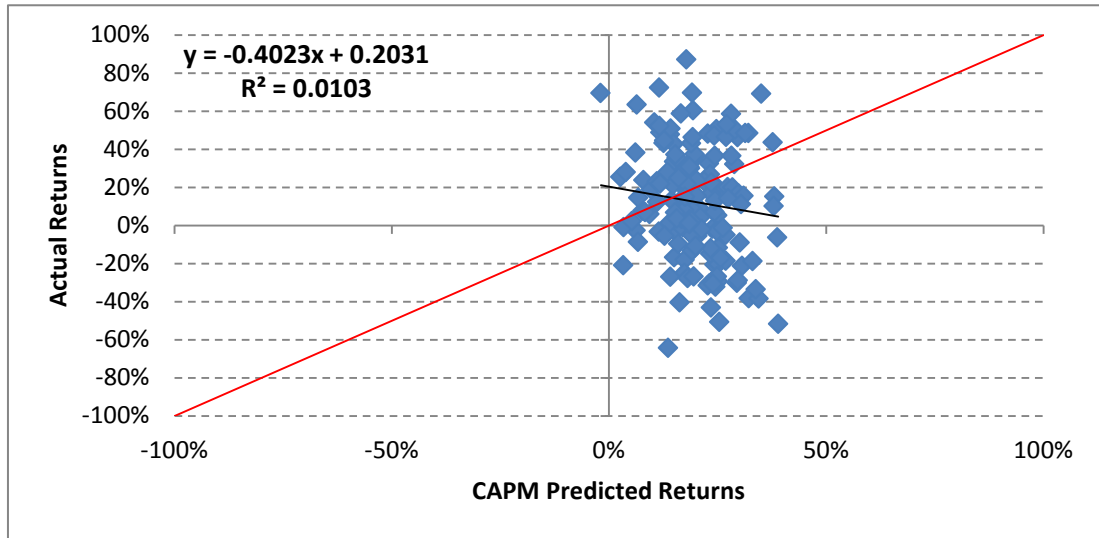


Figure 34: Original CAPM vs Actual Returns, Dimson 24 month beta, 31 Dec 1988 - 31 Dec 1990

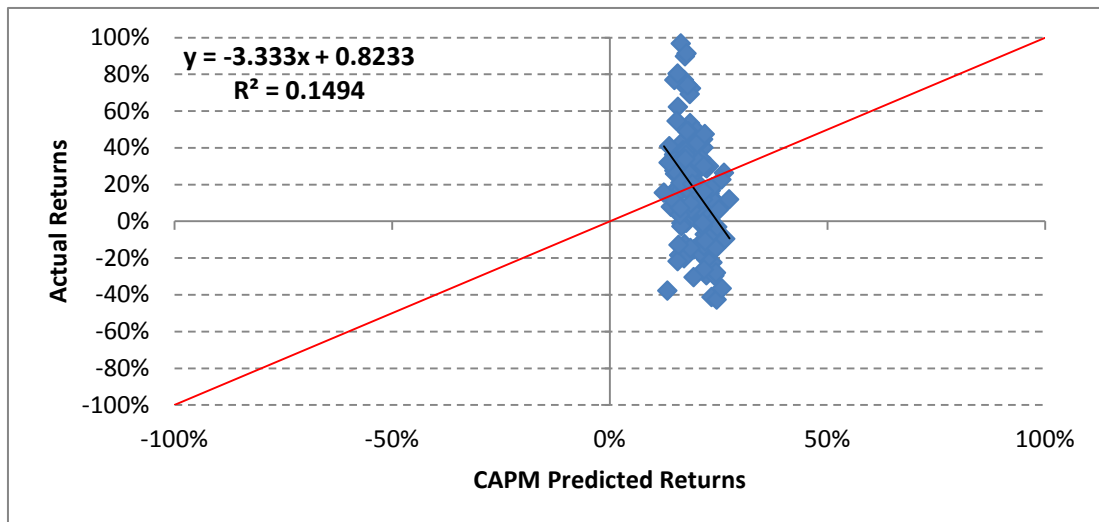


Figure 35: Original CAPM vs Actual Returns, Dimson 24 month beta, 31 Dec 1990 - 31 Dec 1992

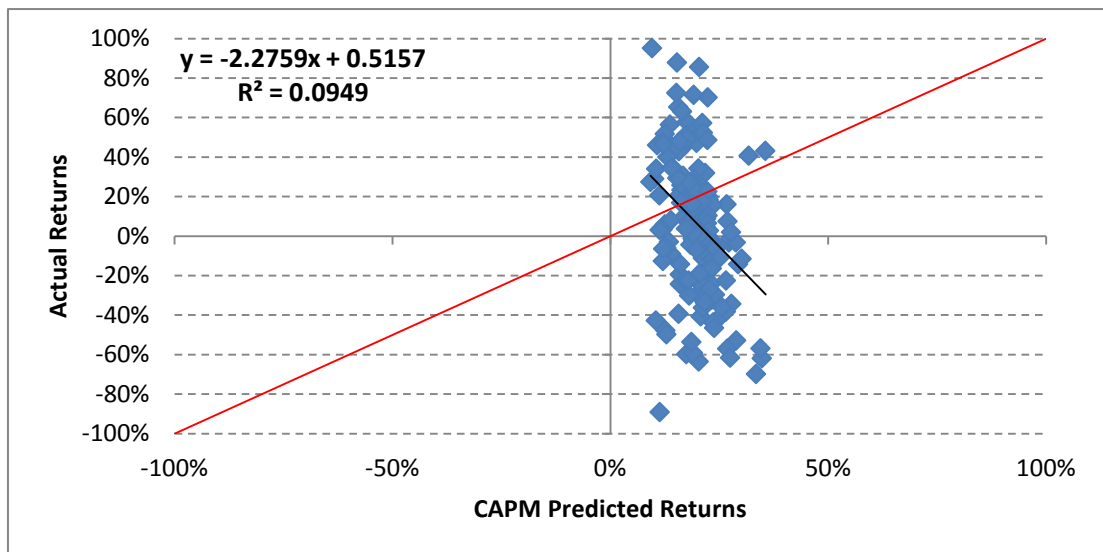


Figure 36: Original CAPM vs Actual Returns, Dimson 24 month beta, 31 Dec 1992 - 31 Dec 1994

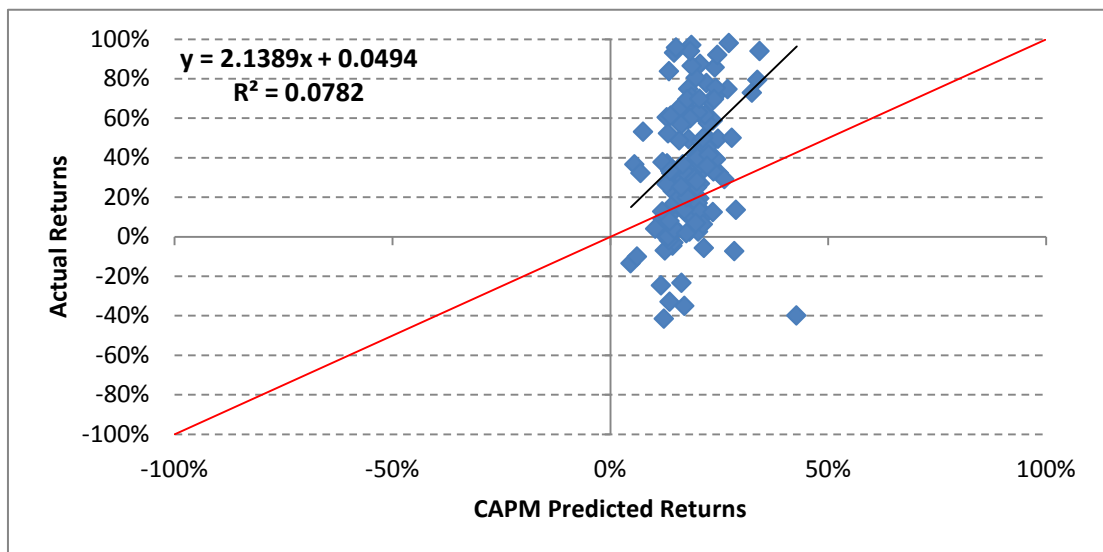


Figure 37: Original CAPM vs Actual Returns, Dimson 24 month beta, 31 Dec 1994 - 31 Dec 1996

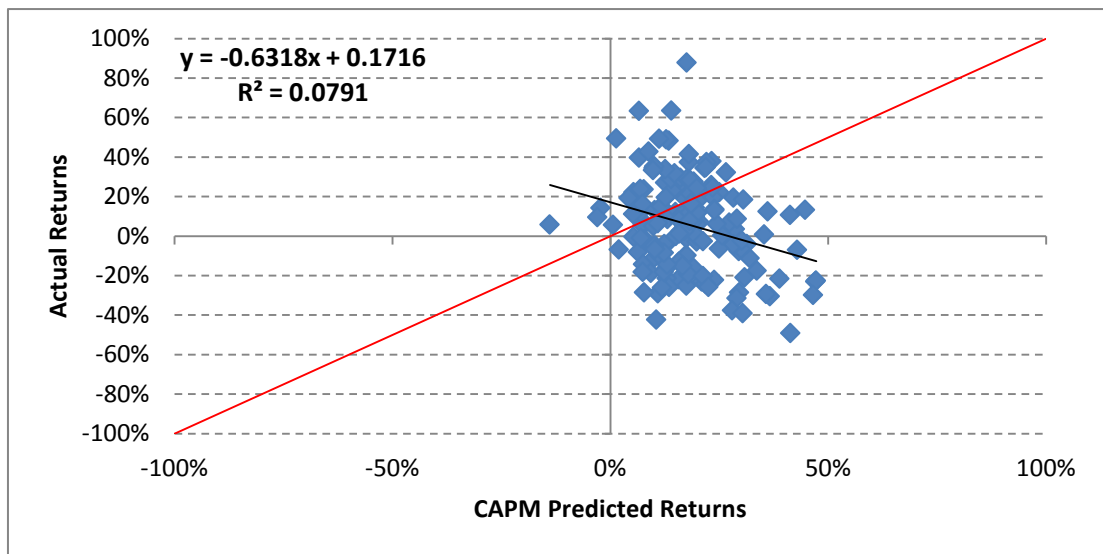


Figure 38: Original CAPM vs Actual Returns, Dimson 24 month beta, 31 Dec 1996 - 31 Dec 1998

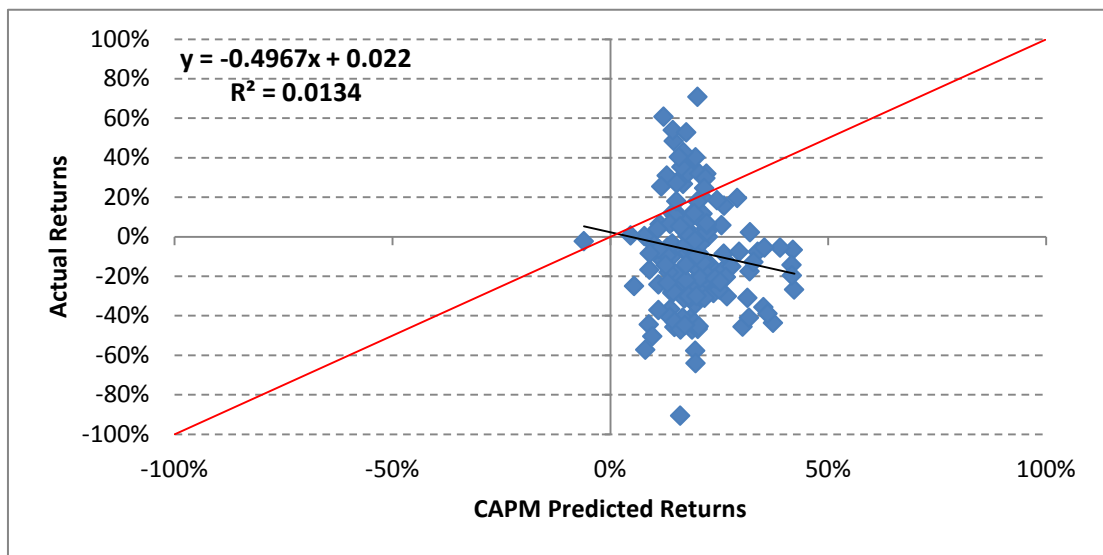


Figure 39: Original CAPM vs Actual Returns, Dimson 24 month beta, 31 Dec 1998 - 31 Dec 2000

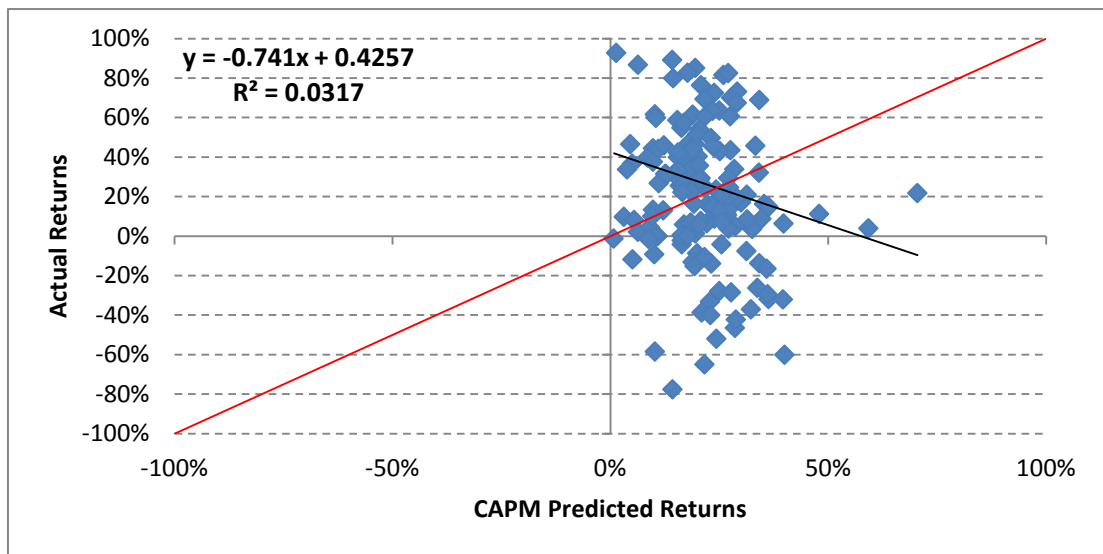


Figure 40: Original CAPM vs Actual Returns, Dimson 24 month beta, 31 Dec 2000 - 31 Dec 2002

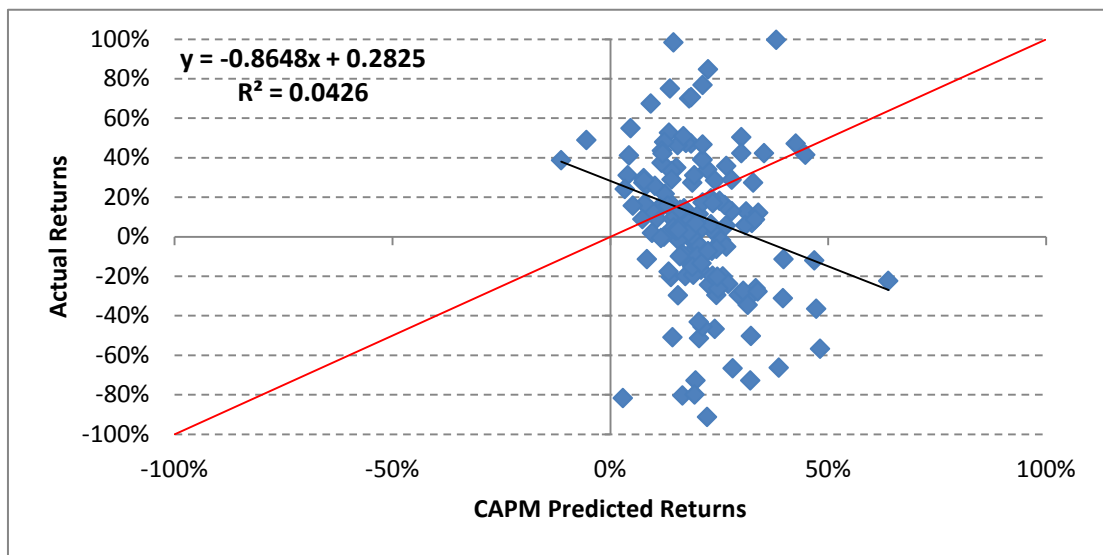


Figure 41: Original CAPM vs Actual Returns, Dimson 24 month beta, 31 Dec 2002 - 31 Dec 2004

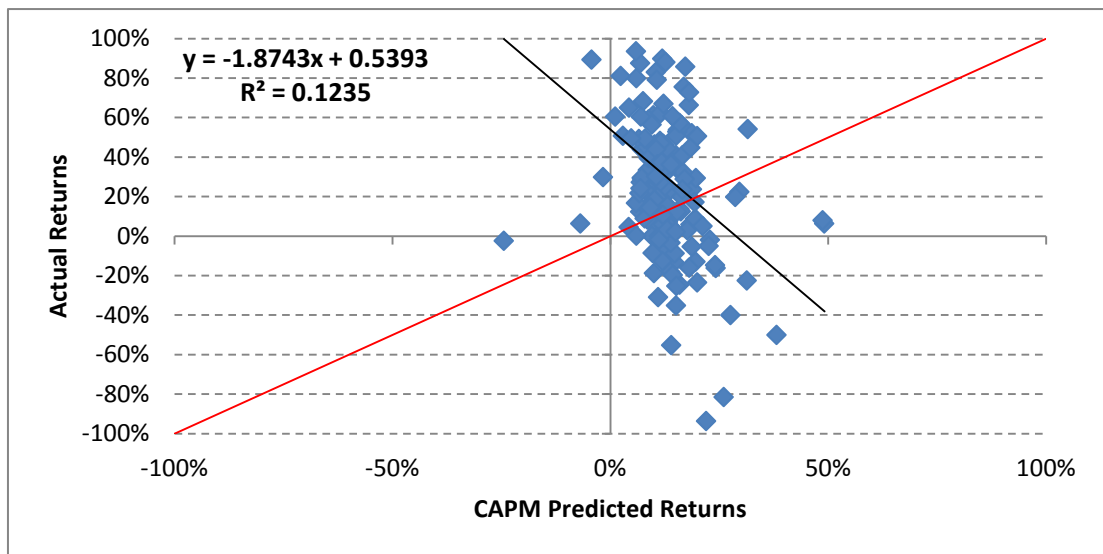


Figure 42: Original CAPM vs Actual Returns, Dimson 24 month beta, 31 Dec 2004 - 31 Dec 2006

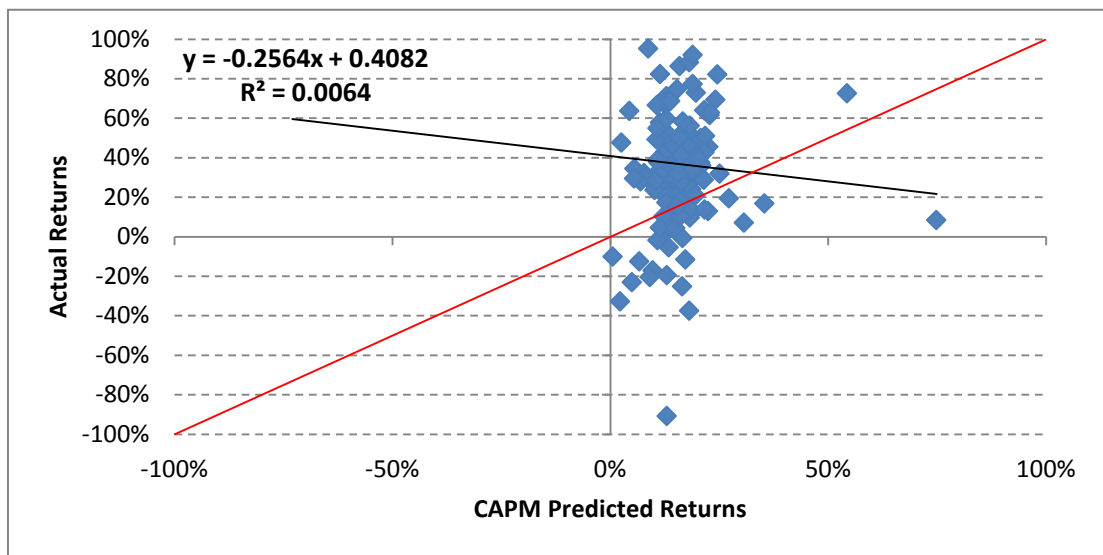


Figure 43: Original CAPM vs Actual Returns, Dimson 24 month beta, 31 Dec 2006 - 31 Dec 2008

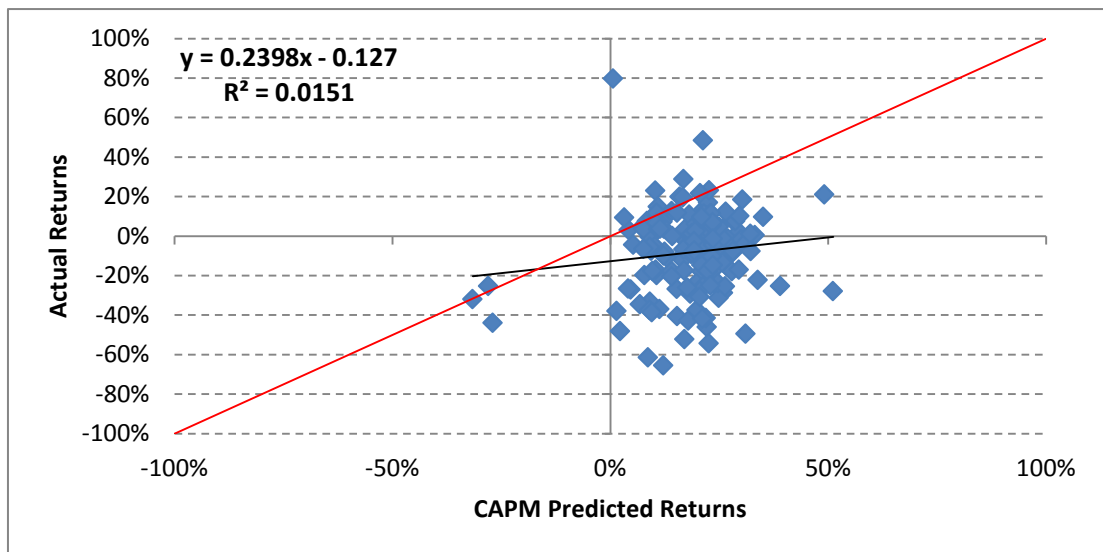


Figure 44: Original CAPM vs Actual Returns, Dimson 24 month beta, 31 Dec 2008 - 31 Dec 2010

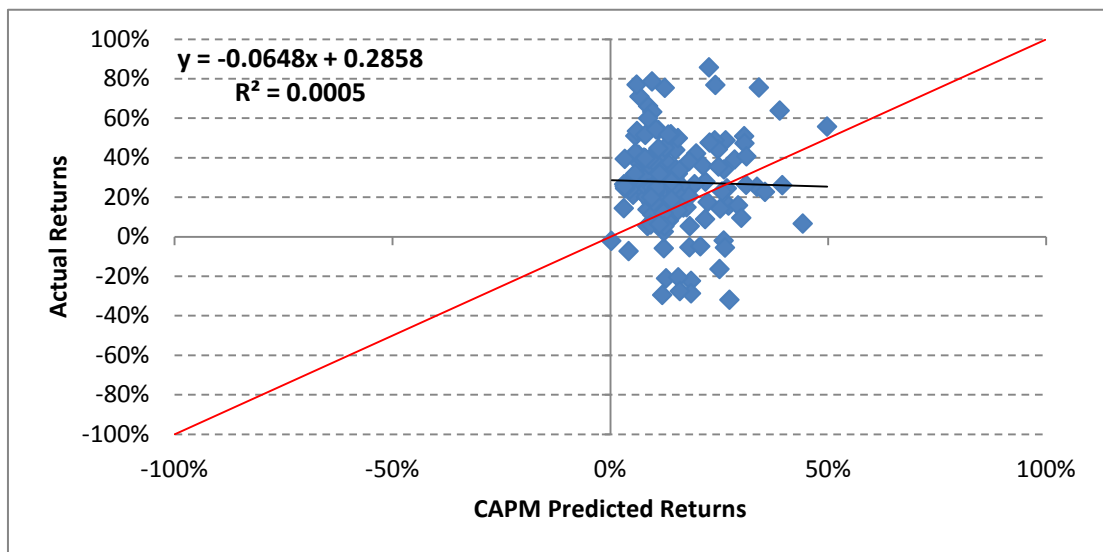


Figure 45: Original CAPM vs Actual Returns, Dimson 24 month beta, 31 Dec 2010 - 31 Dec 2012

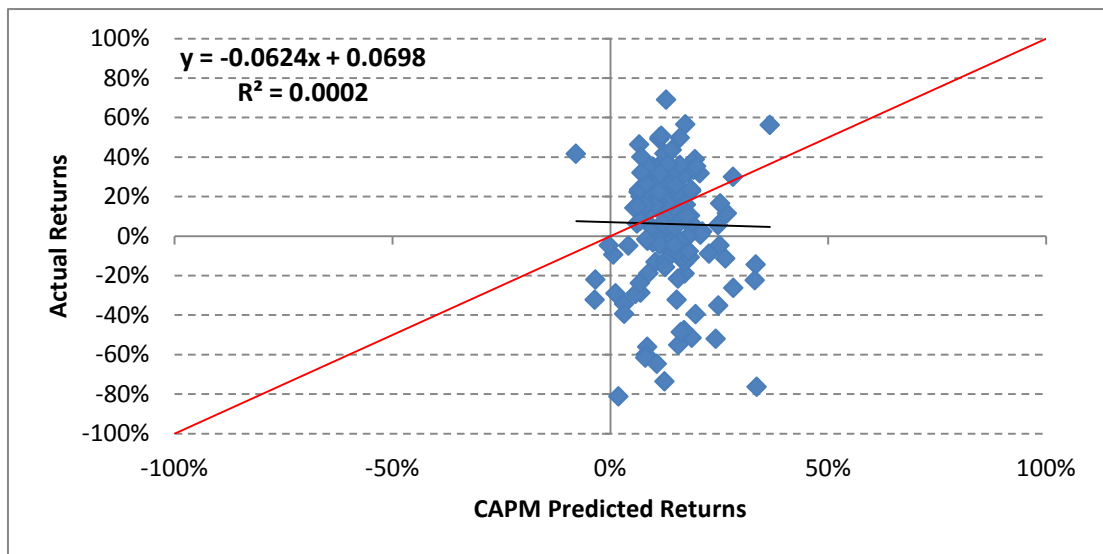
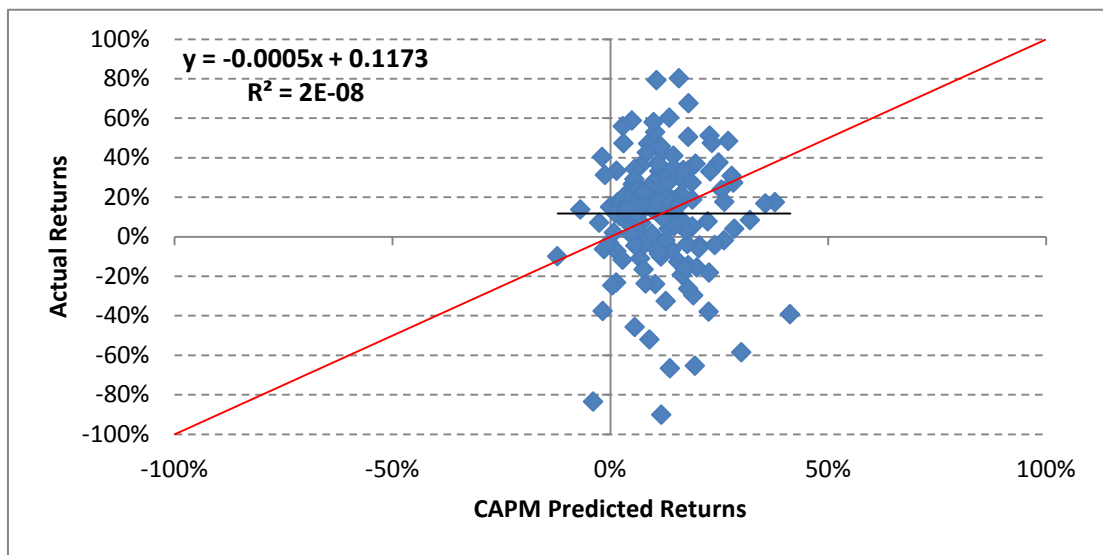


Figure 46: Original CAPM vs Actual Returns, Dimson 24 month beta, 31 Dec 2012 - 31 Dec 2014



Appendix 5 – Graphical Analysis Original CAPM, Dimson 60 month beta

Figure 47: Original CAPM vs Actual Returns, Dimson 60 month beta, 31 Dec 1989 - 31 Dec 1994

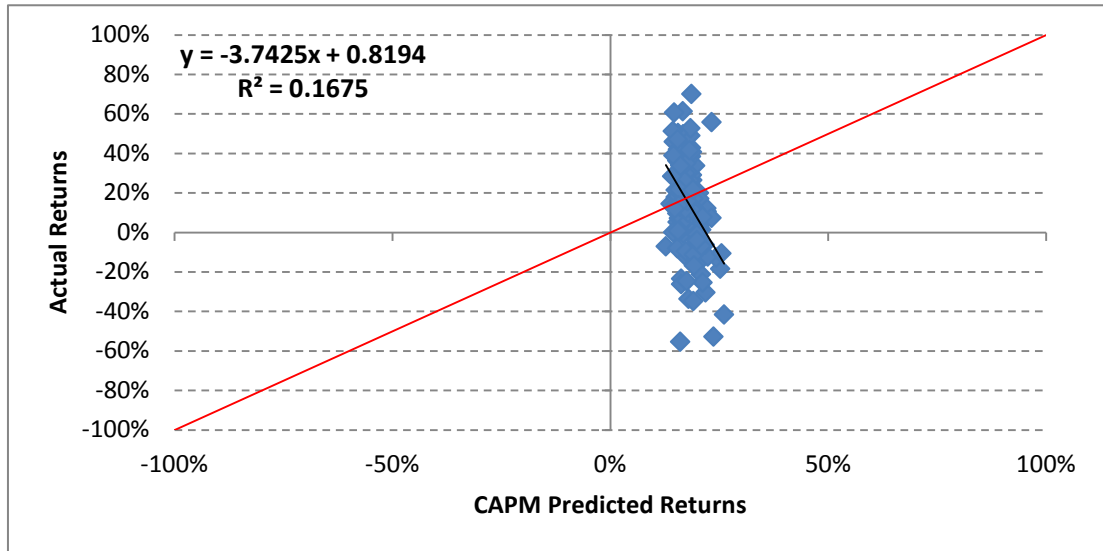


Figure 48: Original CAPM vs Actual Returns, Dimson 60 month beta, 31 Dec 1994 - 31 Dec 1999

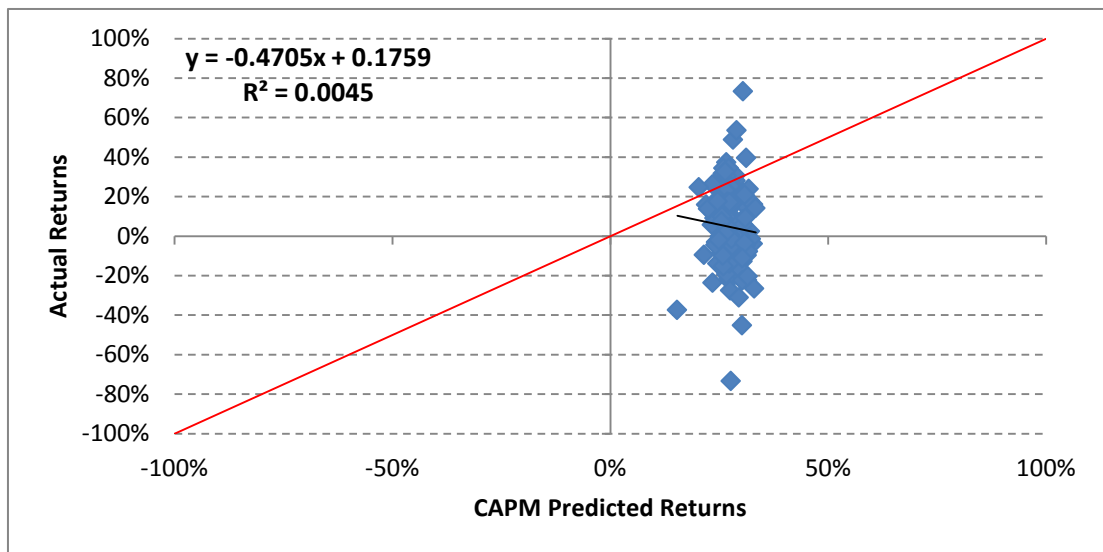


Figure 49: Original CAPM vs Actual Returns, Dimson 60 month beta, 31 Dec 1999 - 31 Dec 2004

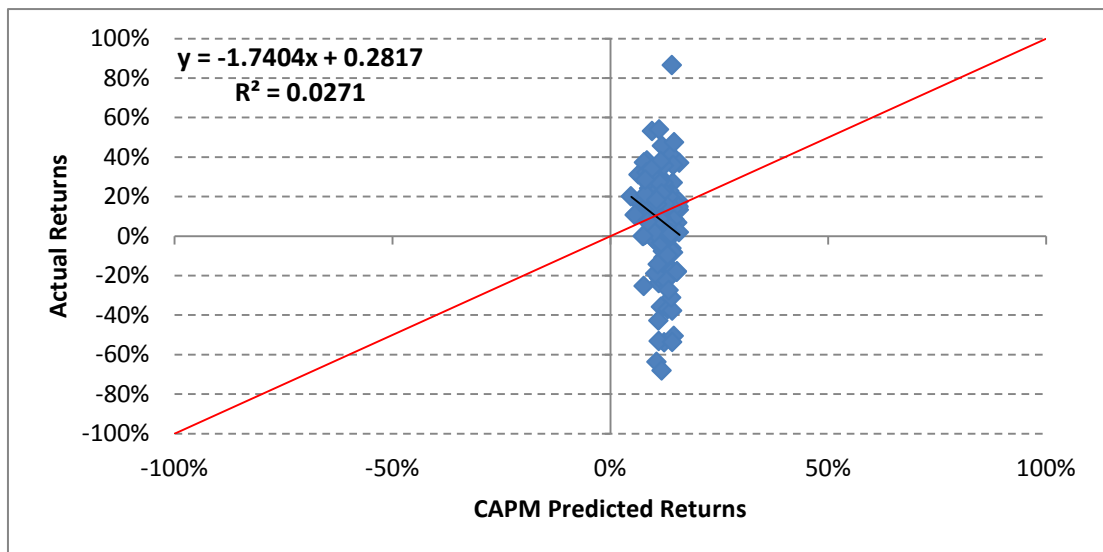


Figure 50: Original CAPM vs Actual Returns, Dimson 60 month beta, 31 Dec 2004 - 31 Dec 2009

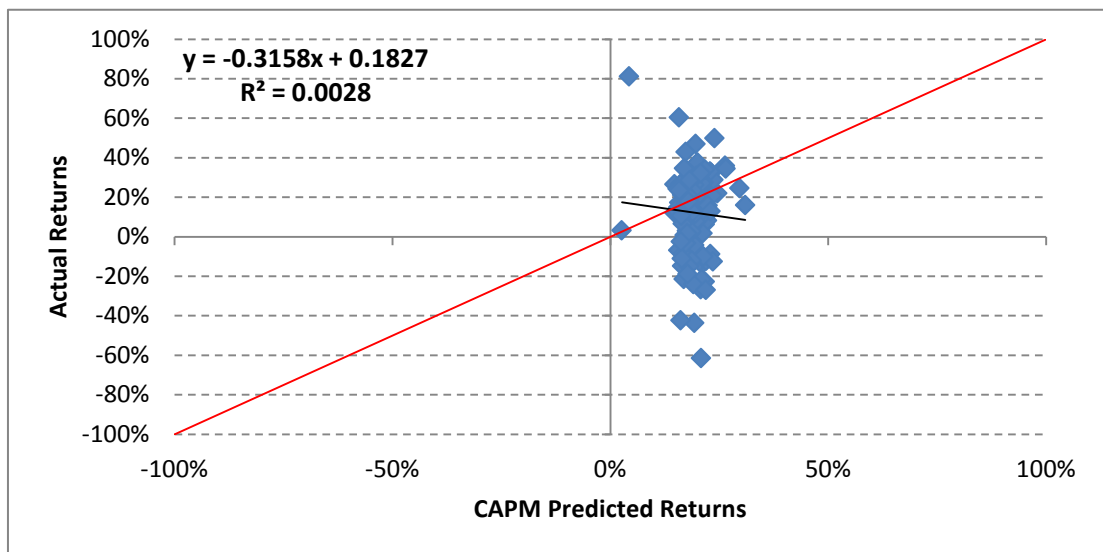
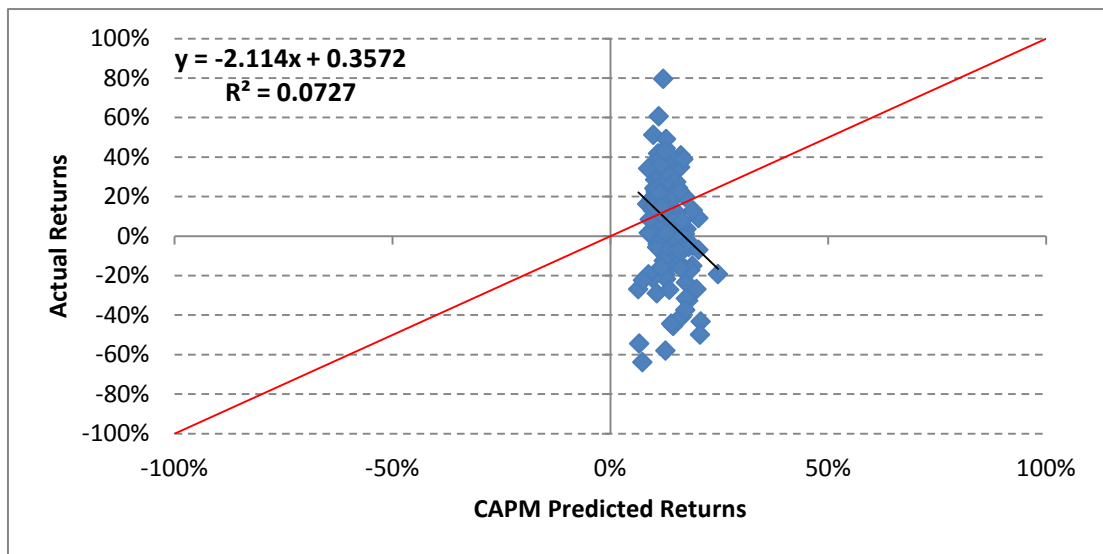


Figure 51: Original CAPM vs Actual Returns, Dimson 60 month beta, 31 Dec 2009 - 31 Dec 2014



Appendix 6 – Graphical Analysis Black’s CAPM, 24 month beta

Figure 52: Black’s CAPM vs Actual Returns, 24 month beta, 31 Dec 1986 - 31 Dec 1988

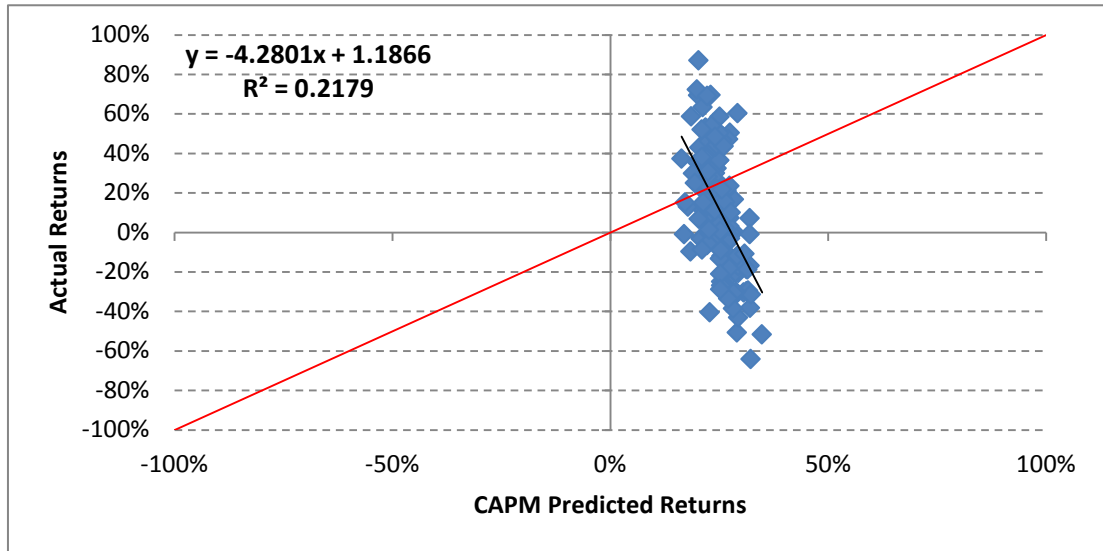


Figure 53: Black’s CAPM vs Actual Returns, 24 month beta, 31 Dec 1988 - 31 Dec 1990

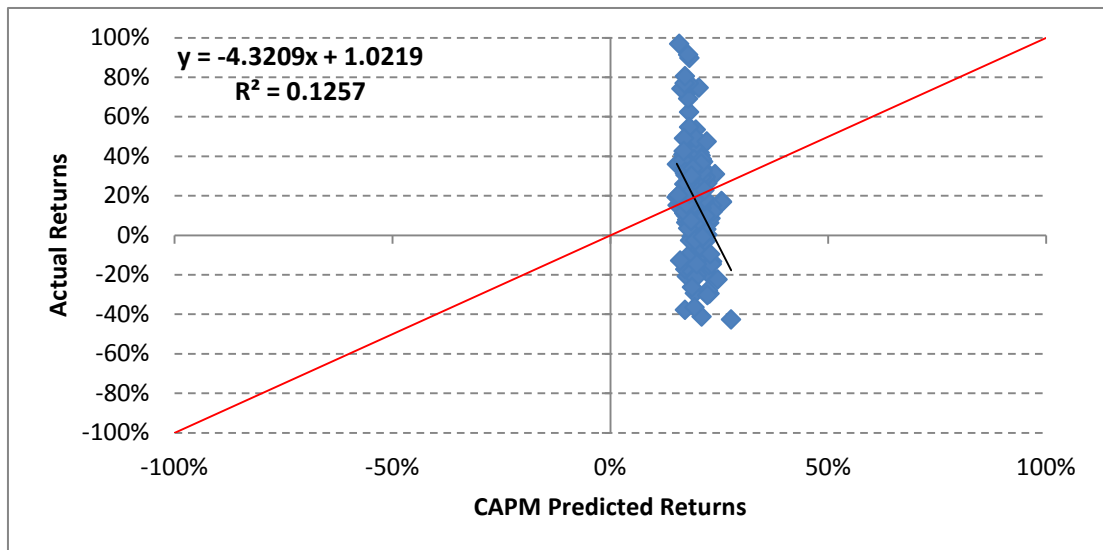


Figure 54: Black's CAPM vs Actual Returns, 24 month beta, 31 Dec 1990 - 31 Dec 1992

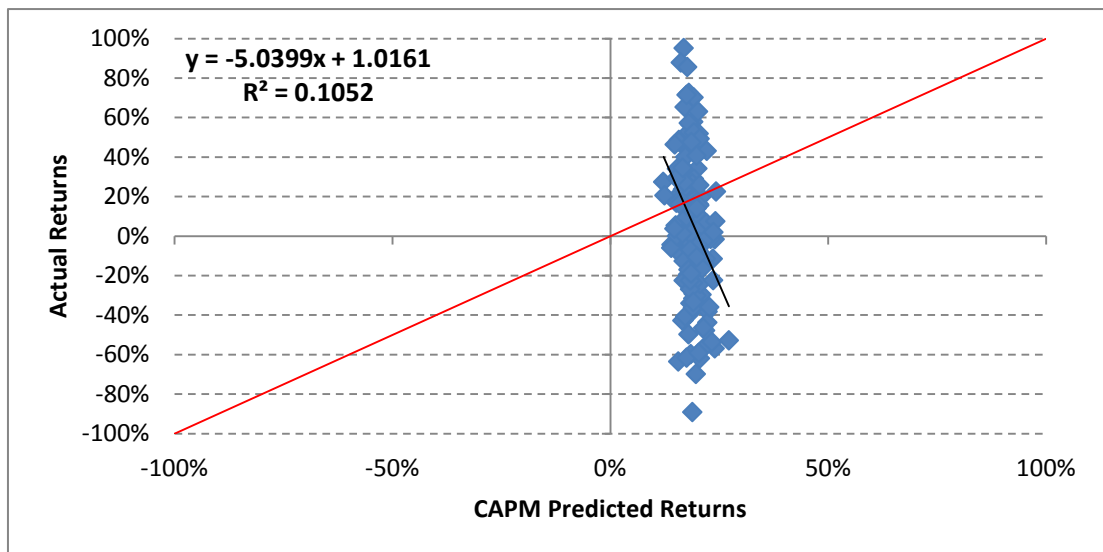


Figure 55: Black's CAPM vs Actual Returns, 24 month beta, 31 Dec 1992 - 31 Dec 1994

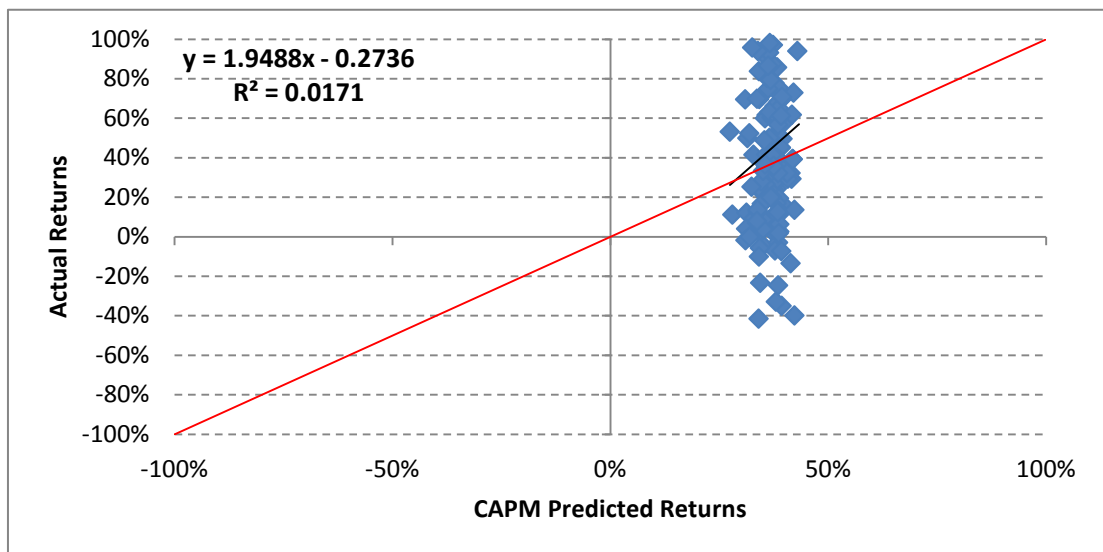


Figure 56: Black's CAPM vs Actual Returns, 24 month beta, 31 Dec 1994 - 31 Dec 1996

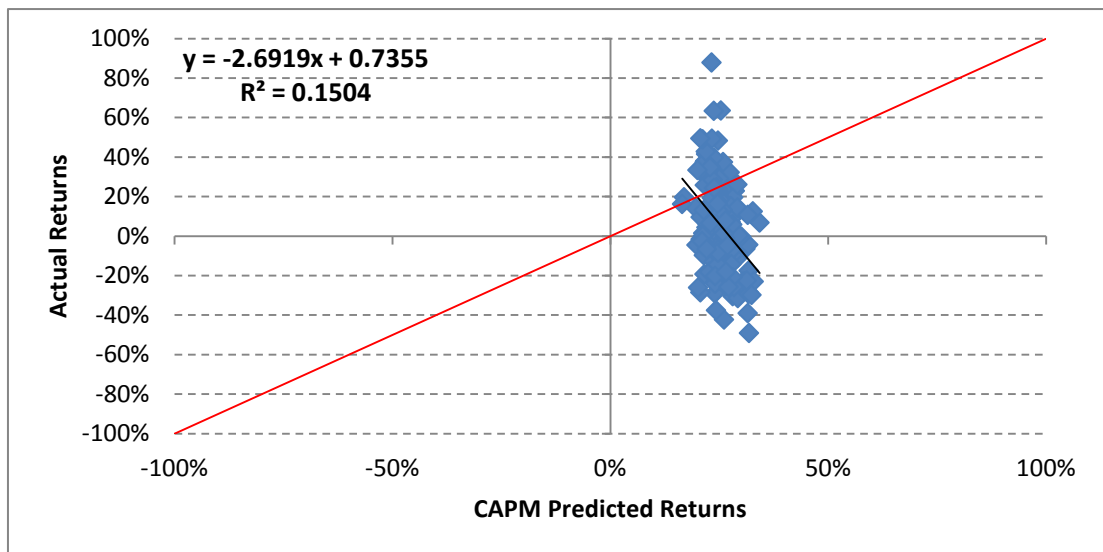


Figure 57: Black's CAPM vs Actual Returns, 24 month beta, 31 Dec 1996 - 31 Dec 1998

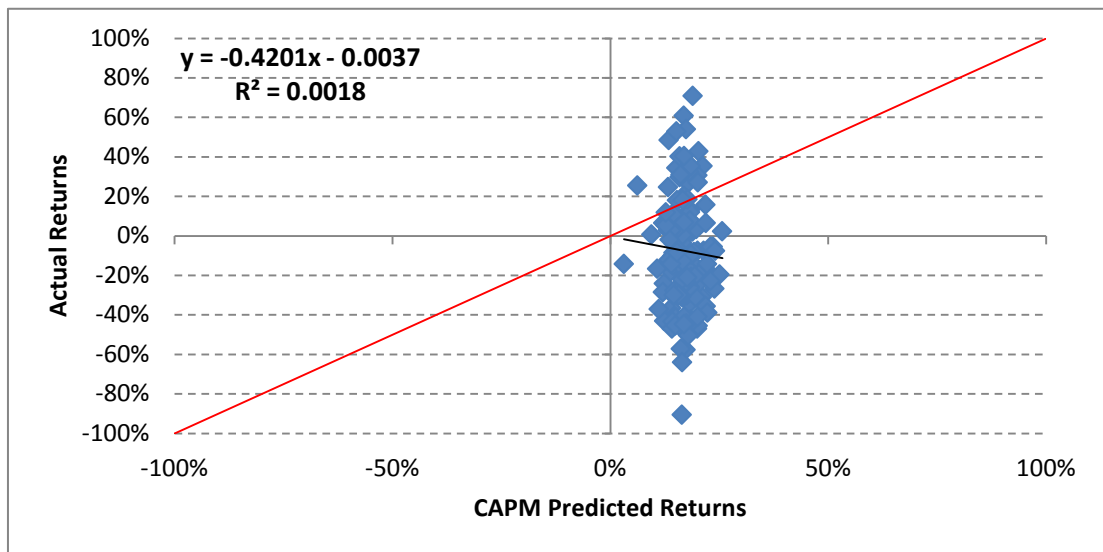


Figure 58: Black's CAPM vs Actual Returns, 24 month beta, 31 Dec 1998 - 31 Dec 2000

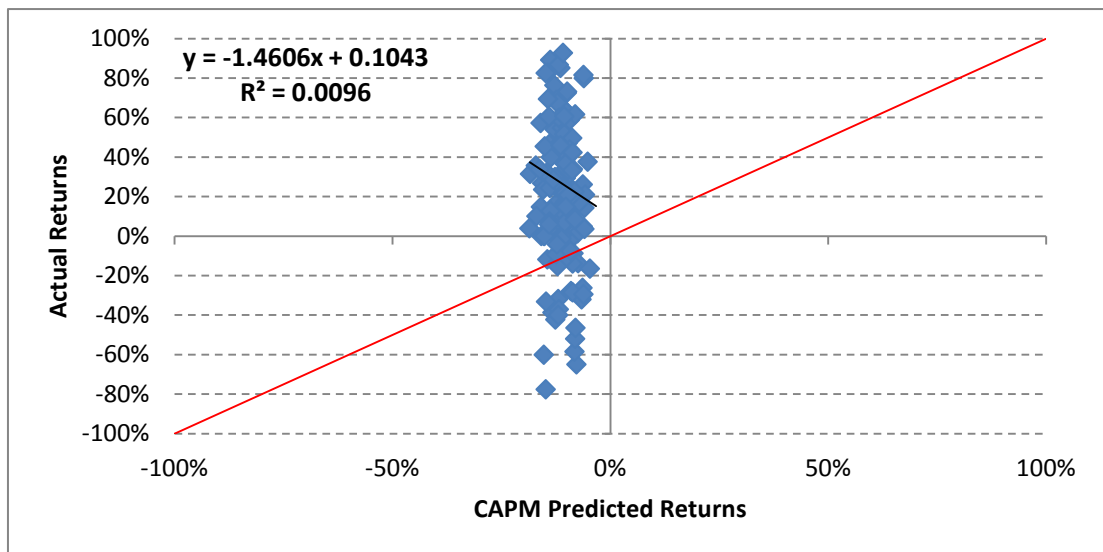


Figure 59: Black's CAPM vs Actual Returns, 24 month beta, 31 Dec 2000 - 31 Dec 2002

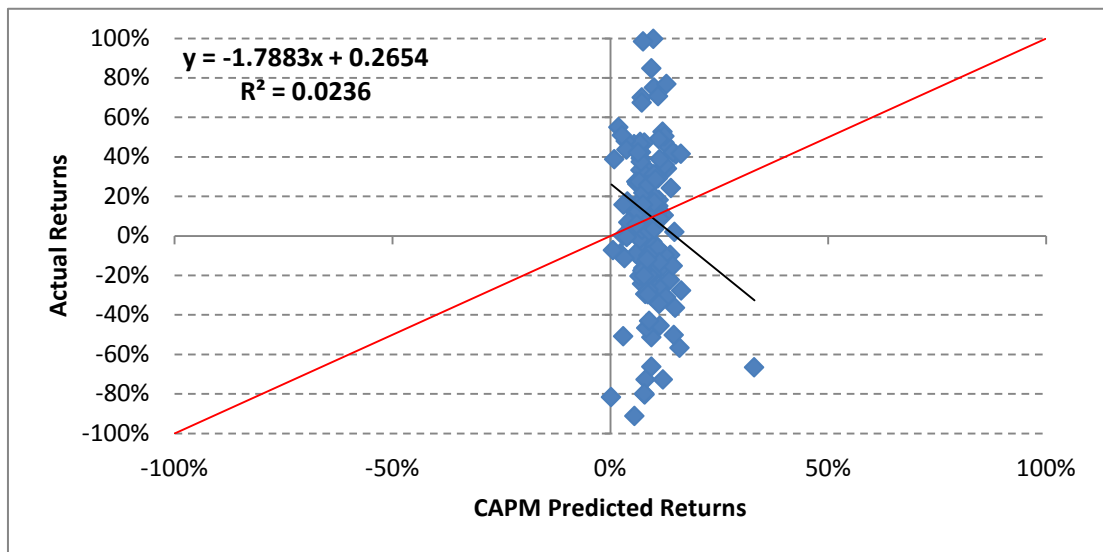


Figure 60: Black's CAPM vs Actual Returns, 24 month beta, 31 Dec 2002 - 31 Dec 2004

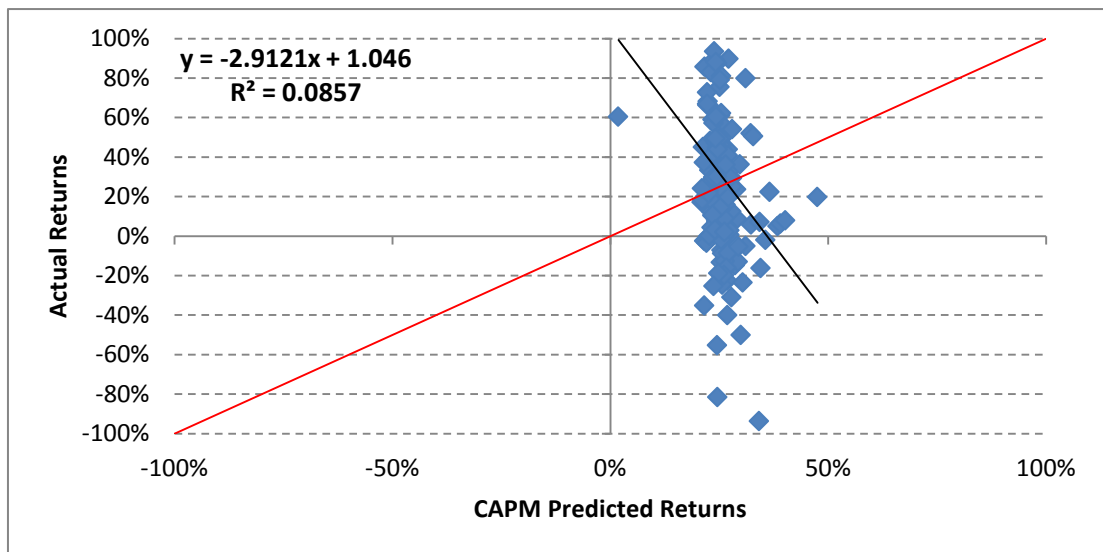


Figure 61: Black's CAPM vs Actual Returns, 24 month beta, 31 Dec 2004 - 31 Dec 2006

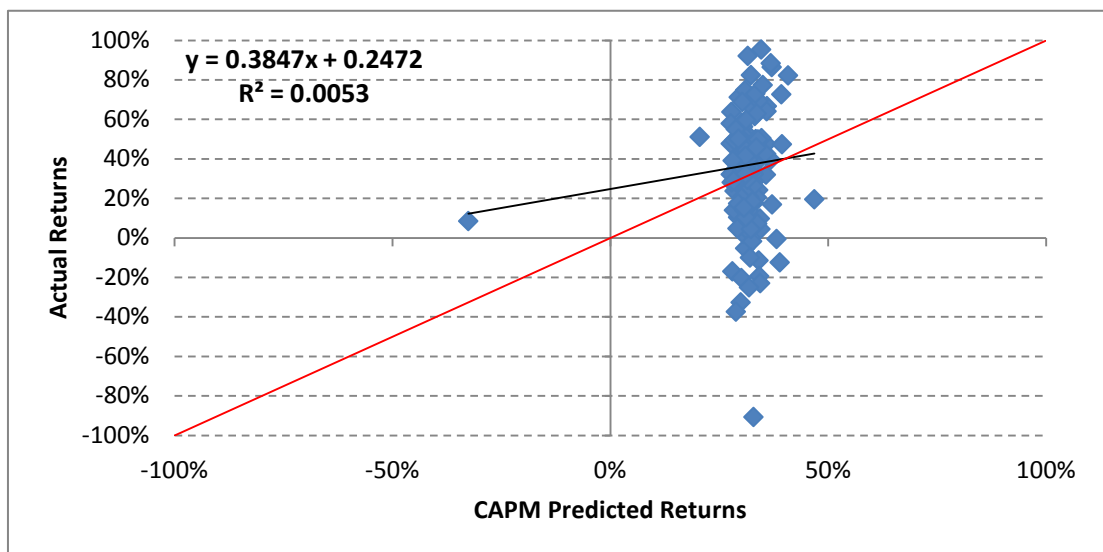


Figure 62: Black's CAPM vs Actual Returns, 24 month beta, 31 Dec 2006 - 31 Dec 2008

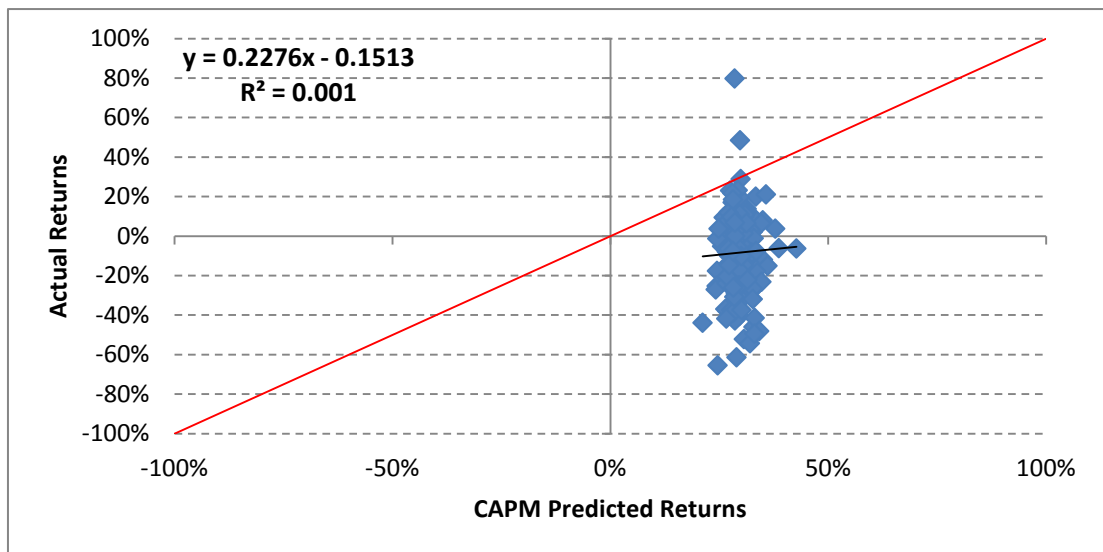


Figure 63: Black's CAPM vs Actual Returns, 24 month beta, 31 Dec 2008 - 31 Dec 2010

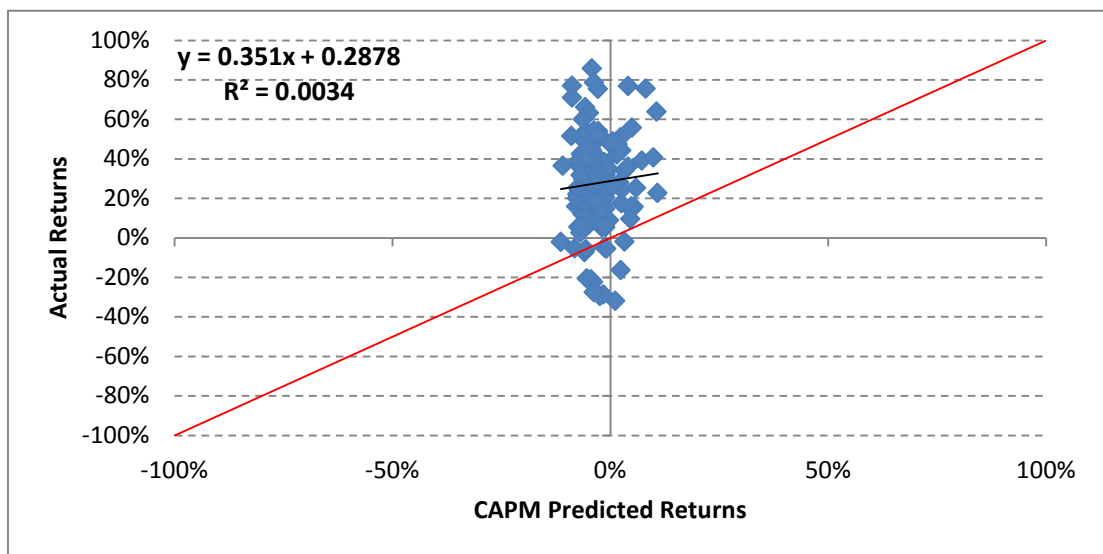


Figure 64: Black's CAPM vs Actual Returns, 24 month beta, 31 Dec 2010 - 31 Dec 2012

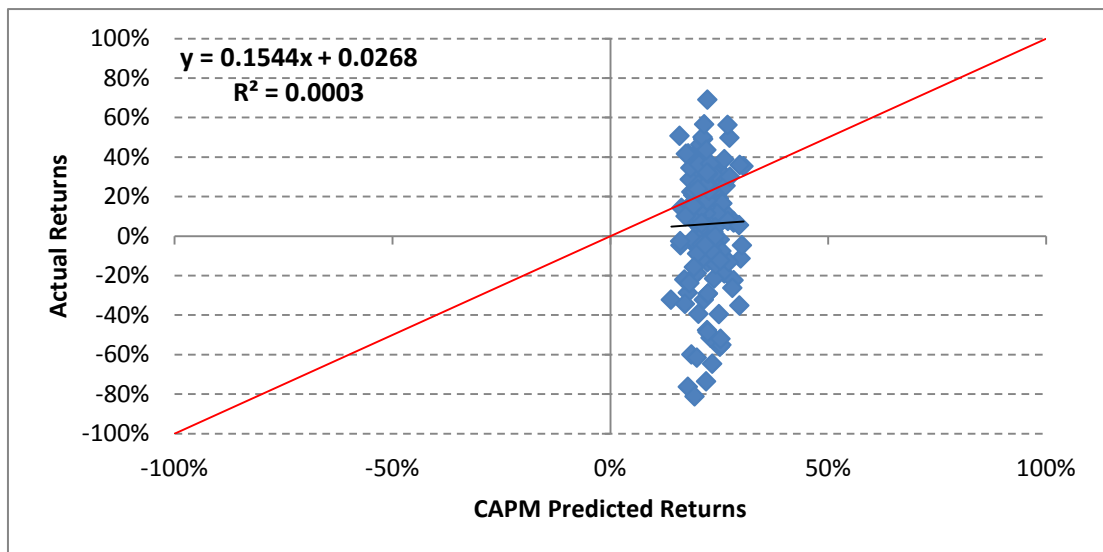
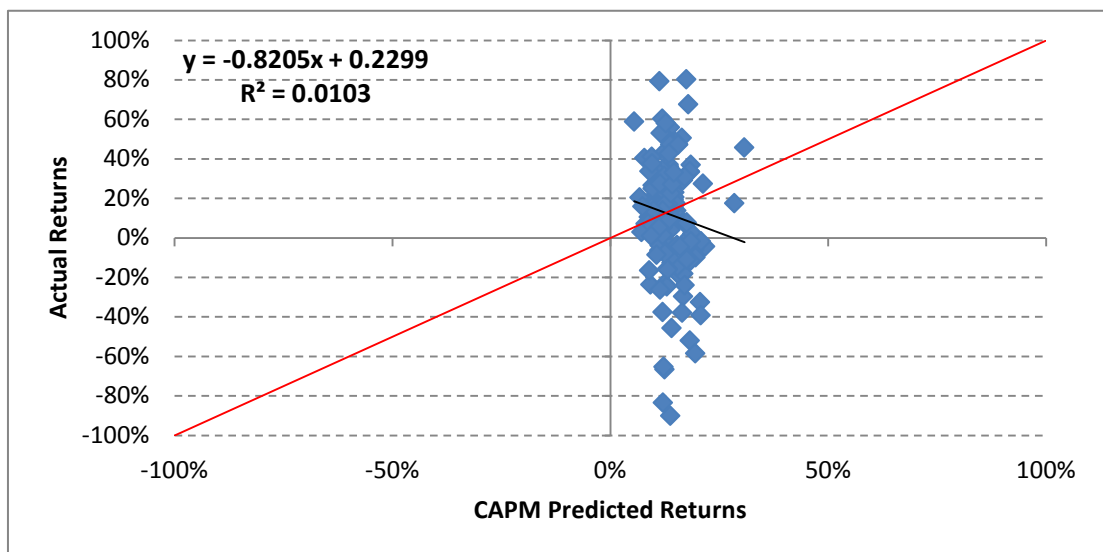


Figure 65: Black's CAPM vs Actual Returns, 24 month beta, 31 Dec 2012 - 31 Dec 2014



Appendix 7 – Graphical Analysis Black’s CAPM, 60 month beta

Figure 66: Black’s CAPM vs Actual Returns, 60 month beta, 31 Dec 1989 - 31 Dec 1994

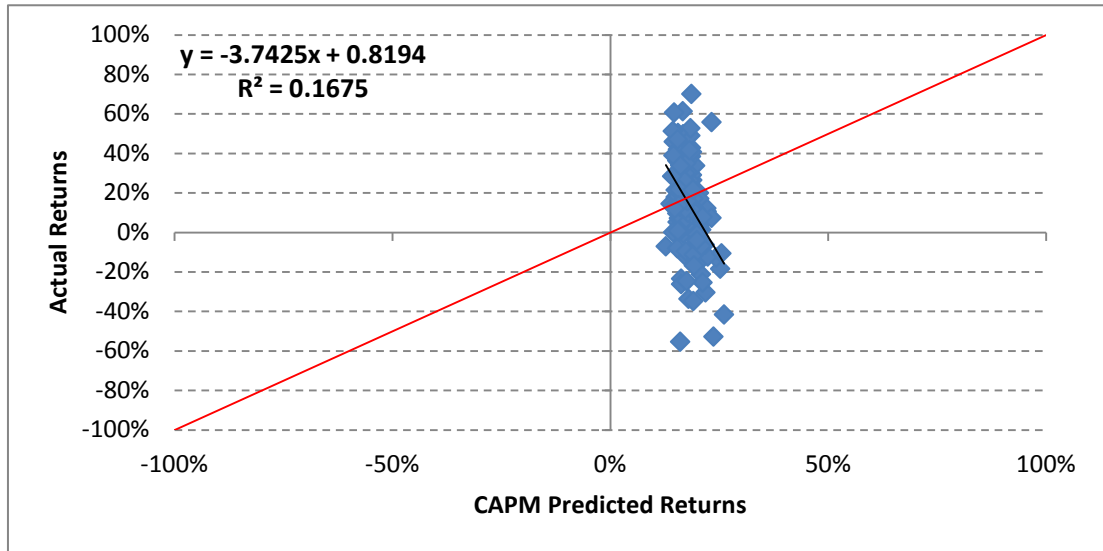


Figure 67: Black’s CAPM vs Actual Returns, 60 month beta, 31 Dec 1994 - 31 Dec 1999

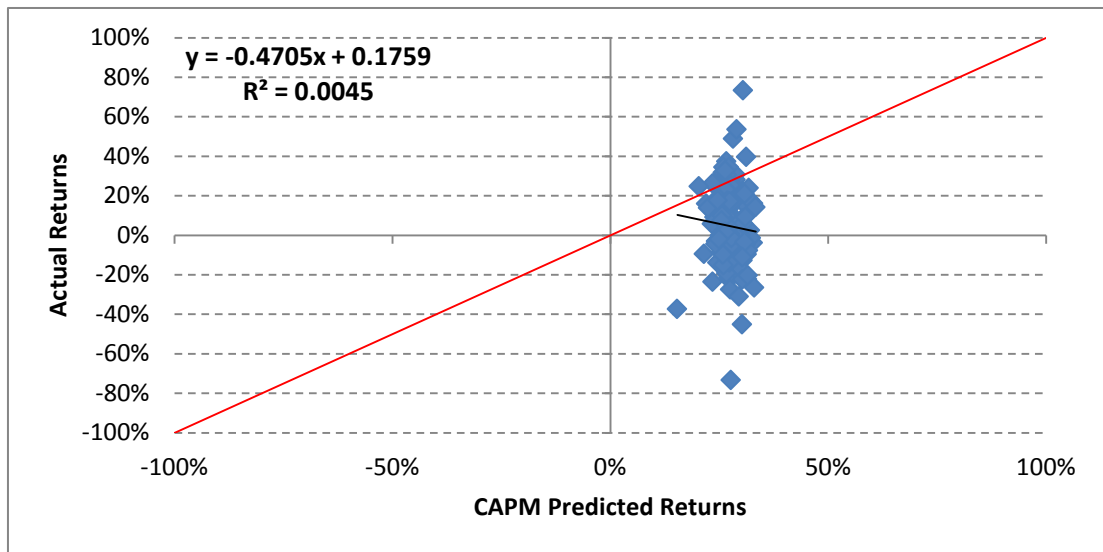


Figure 68: Black's CAPM vs Actual Returns, 60 month beta, 31 Dec 1999 - 31 Dec 2004

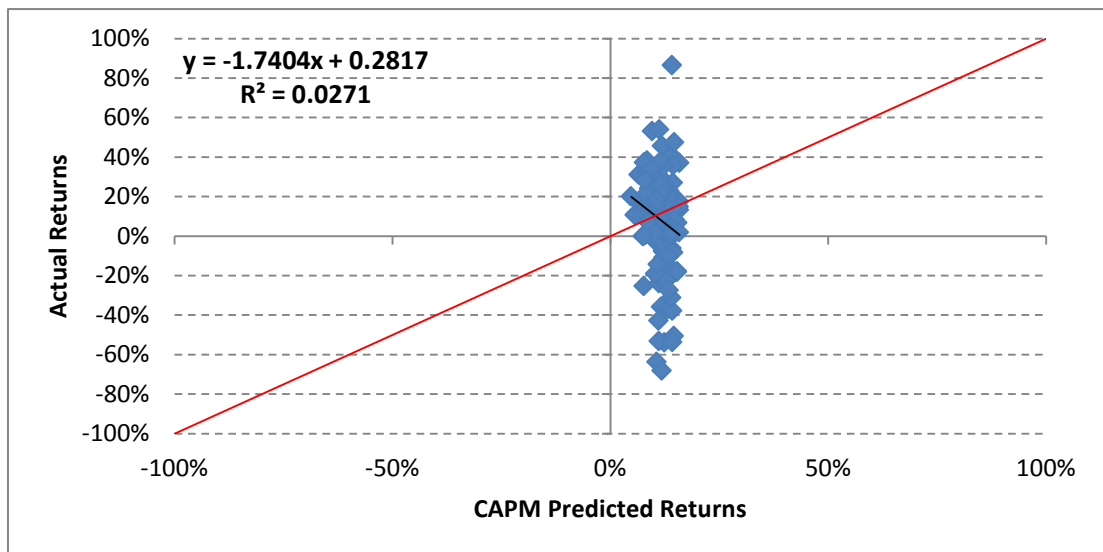


Figure 69: Black's CAPM vs Actual Returns, 60 month beta, 31 Dec 2004 - 31 Dec 2009

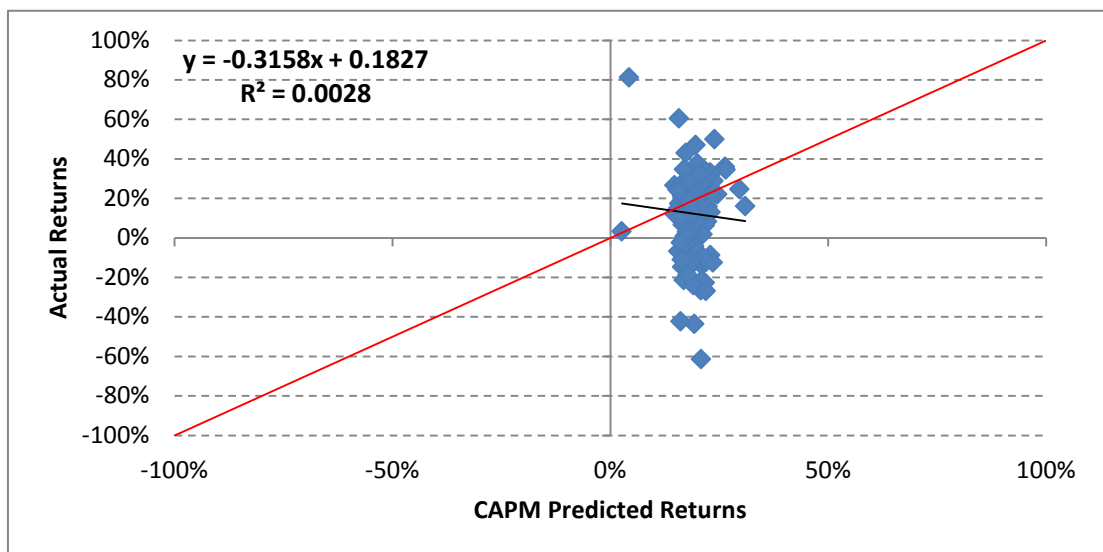
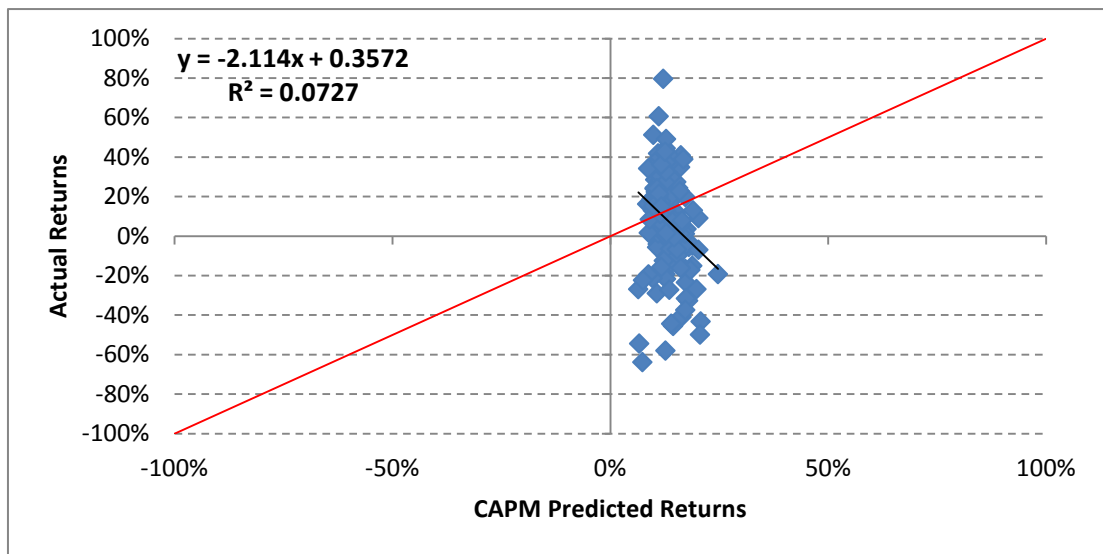


Figure 70: Black's CAPM vs Actual Returns, 60 month beta, 31 Dec 2009 - 31 Dec 2014



Appendix 8 – Graphical Analysis Black’s CAPM, Dimson 24 month beta

Figure 71: Black’s CAPM vs Actual Returns, Dimson 24 month beta, 31 Dec 1986 - 31 Dec 1988

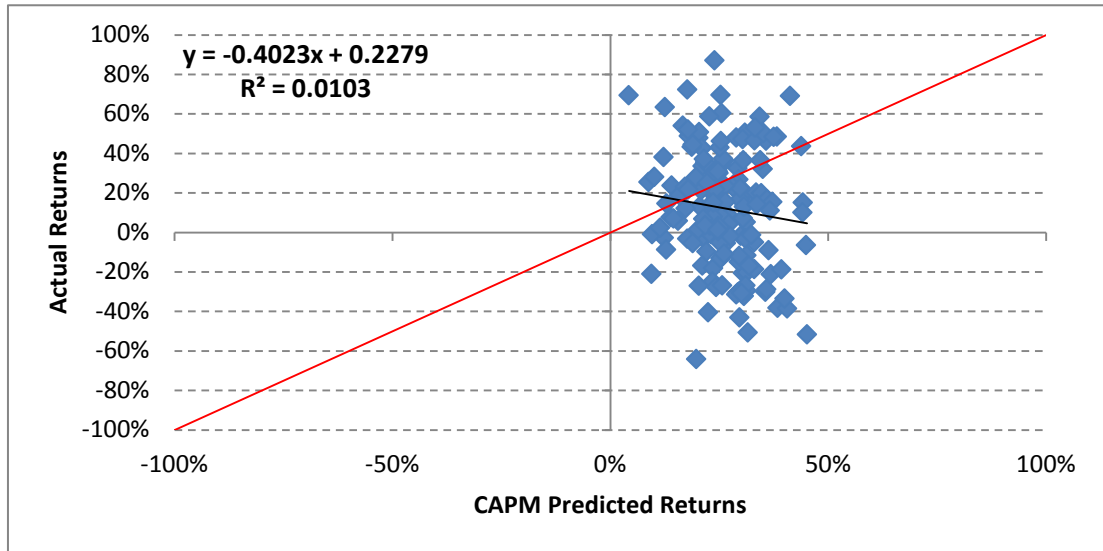


Figure 72: Black’s CAPM vs Actual Returns, Dimson 24 month beta, 31 Dec 1988 - 31 Dec 1990

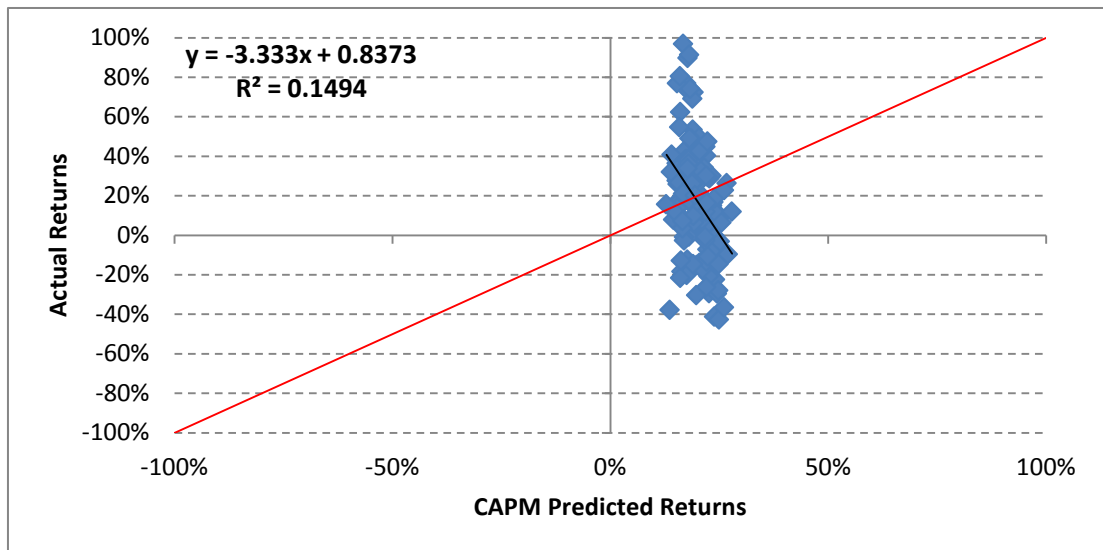


Figure 73: Black's CAPM vs Actual Returns, Dimson 24 month beta, 31 Dec 1990 - 31 Dec 1992

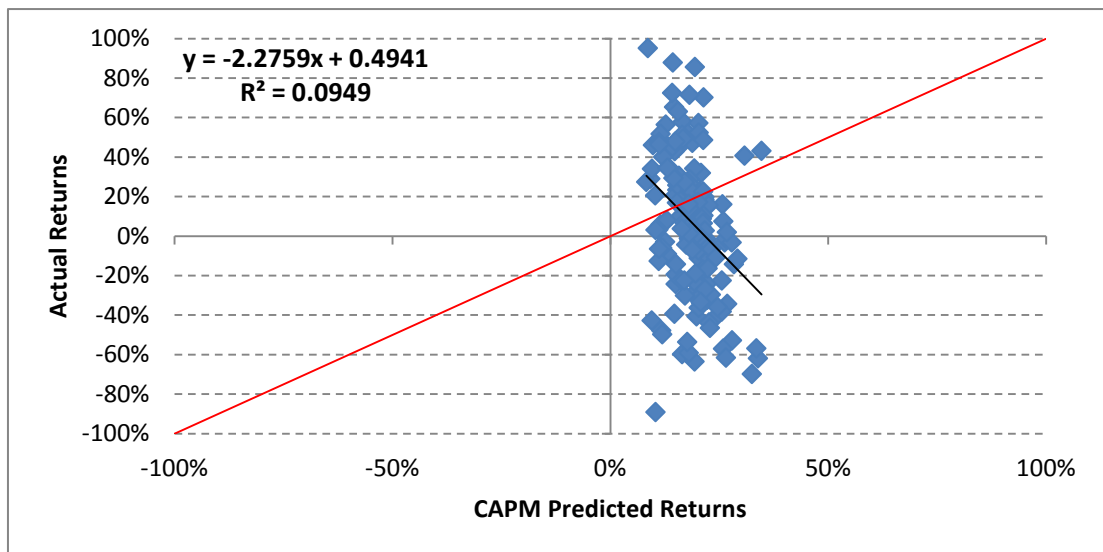


Figure 74: Black's CAPM vs Actual Returns, Dimson 24 month beta, 31 Dec 1992 - 31 Dec 1994

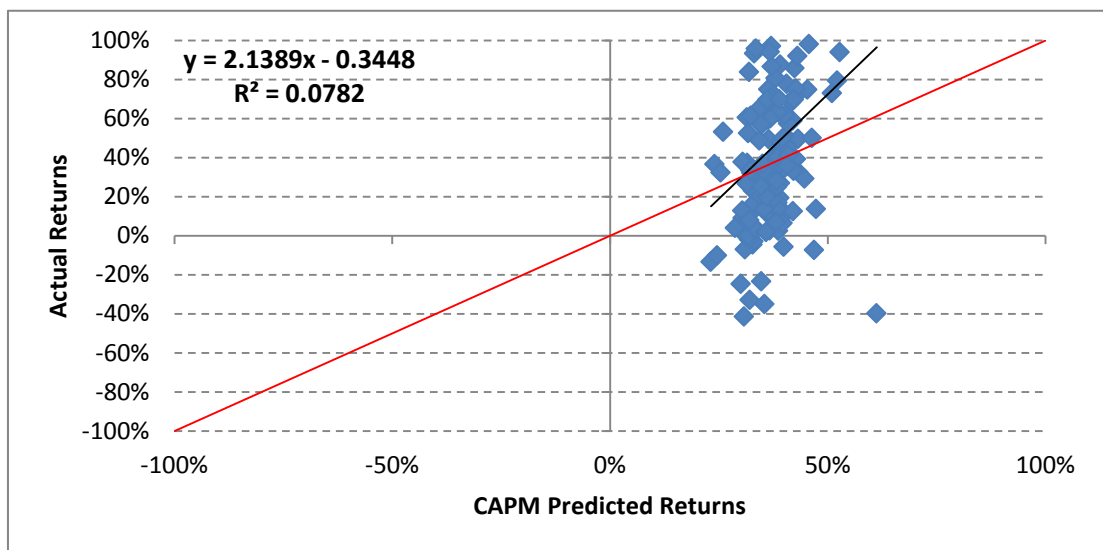


Figure 75: Black's CAPM vs Actual Returns, Dimson 24 month beta, 31 Dec 1994 - 31 Dec 1996

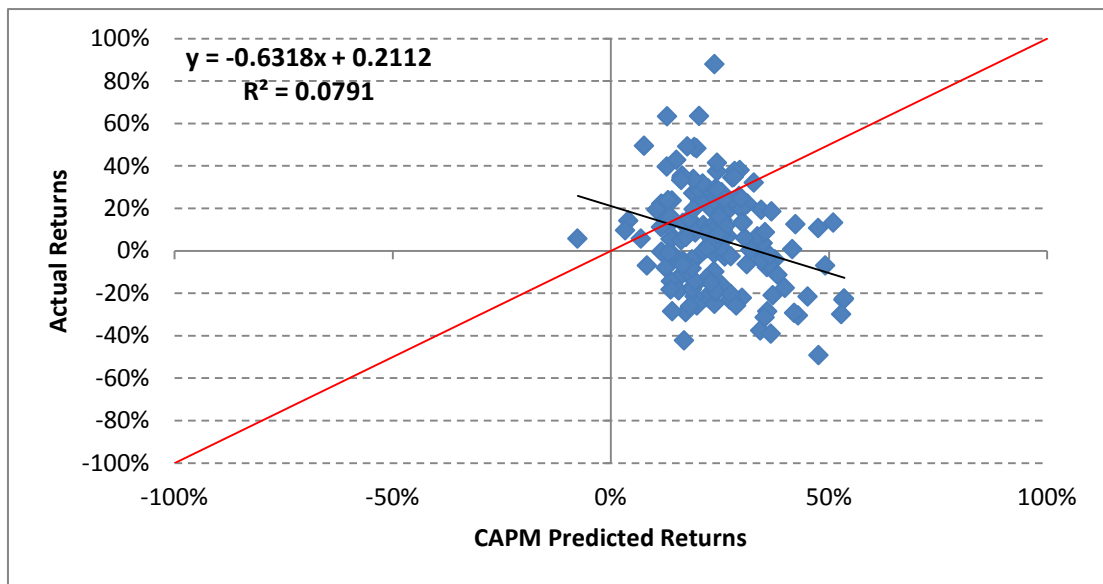


Figure 76: Black's CAPM vs Actual Returns, Dimson 24 month beta, 31 Dec 1996 - 31 Dec 1998

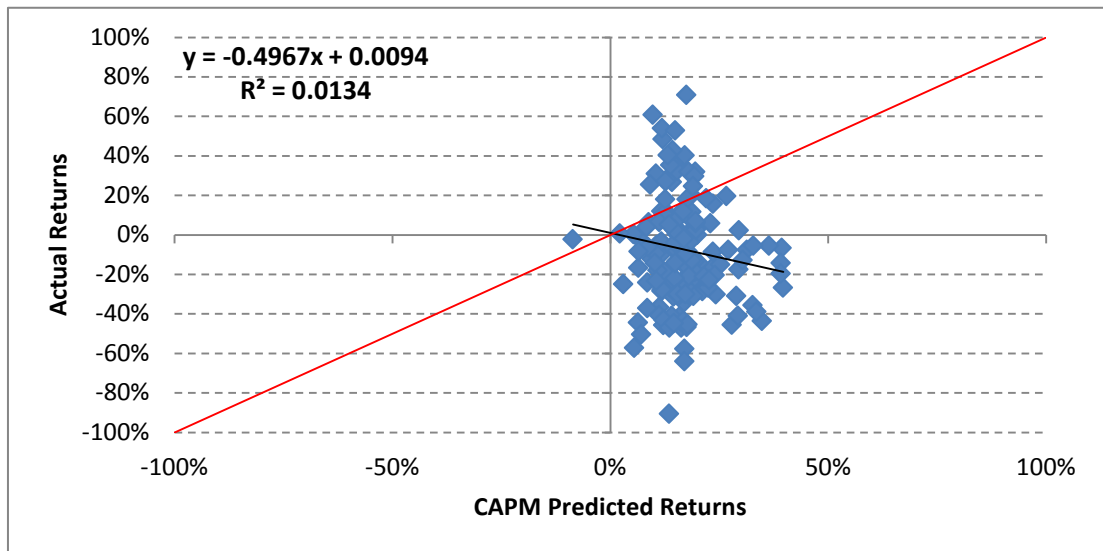


Figure 77: Black's CAPM vs Actual Returns, Dimson 24 month beta, 31 Dec 1998 - 31 Dec 2000

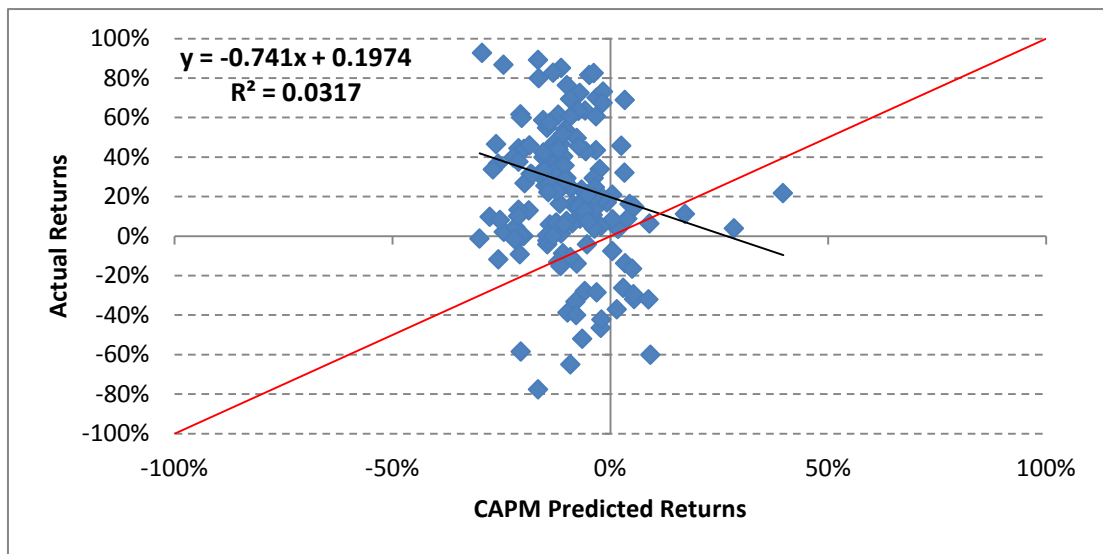


Figure 78: Black's CAPM vs Actual Returns, Dimson 24 month beta, 31 Dec 2000 - 31 Dec 2002

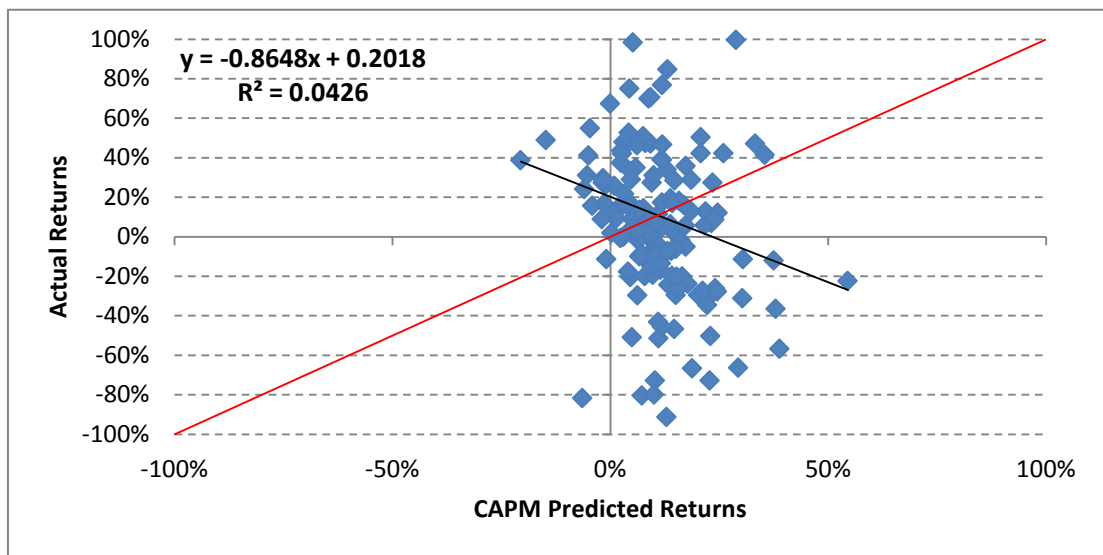


Figure 79: Black's CAPM vs Actual Returns, Dimson 24 month beta, 31 Dec 2002 - 31 Dec 2004

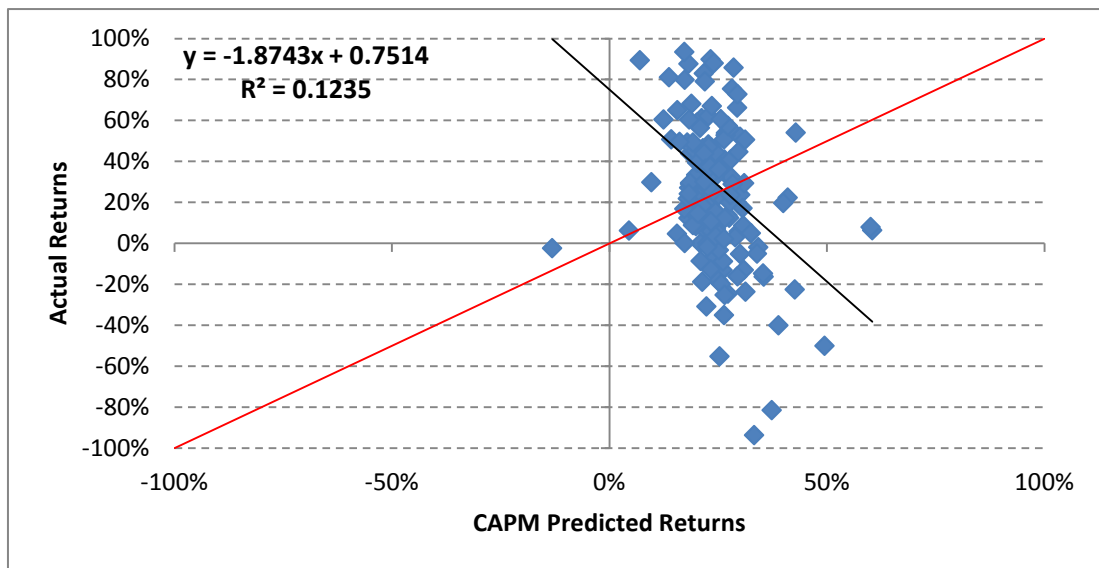


Figure 80: Black's CAPM vs Actual Returns, Dimson 24 month beta, 31 Dec 2004 - 31 Dec 2006

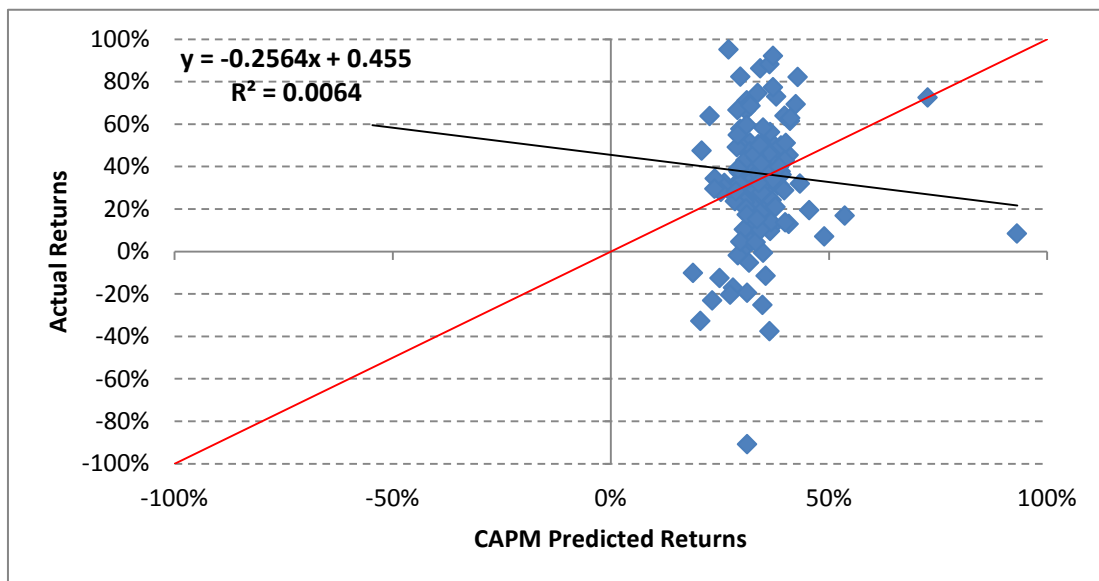


Figure 81: Black's CAPM vs Actual Returns, Dimson 24 month beta, 31 Dec 2006 - 31 Dec 2008

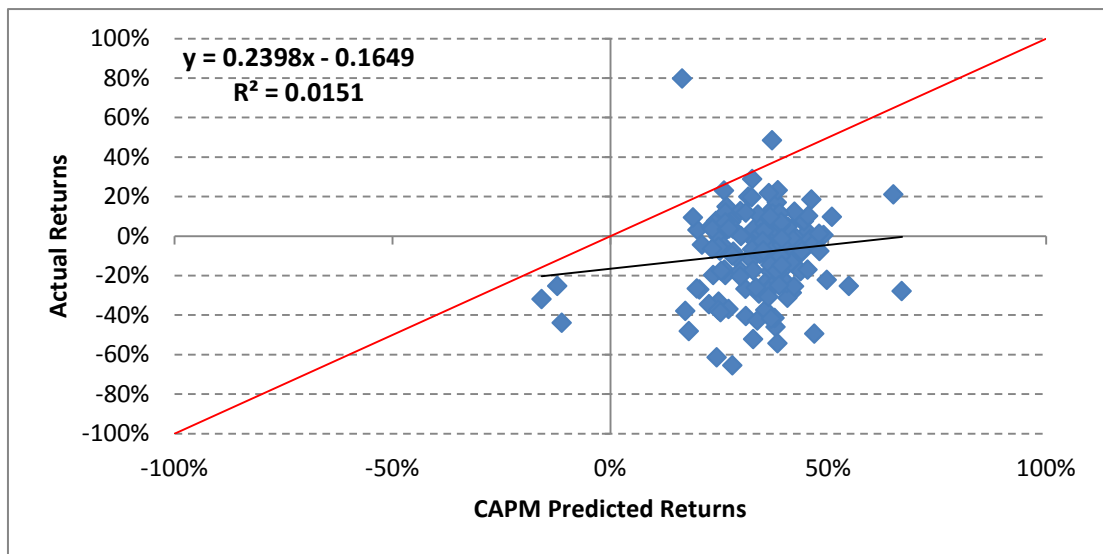


Figure 82: Black's CAPM vs Actual Returns, Dimson 24 month beta, 31 Dec 2008 - 31 Dec 2010

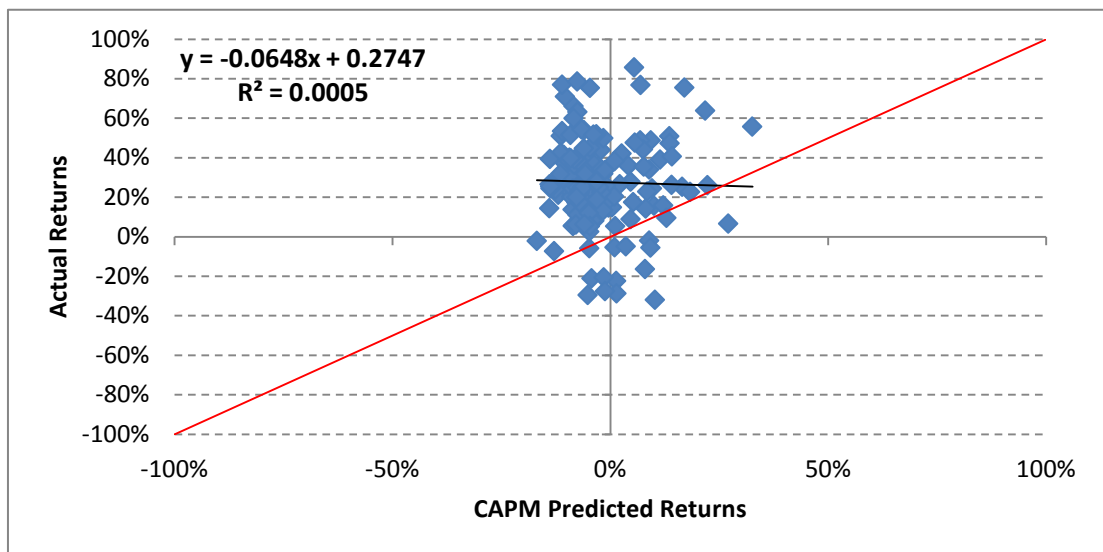


Figure 83: Black's CAPM vs Actual Returns, Dimson 24 month beta, 31 Dec 2010 - 31 Dec 2012

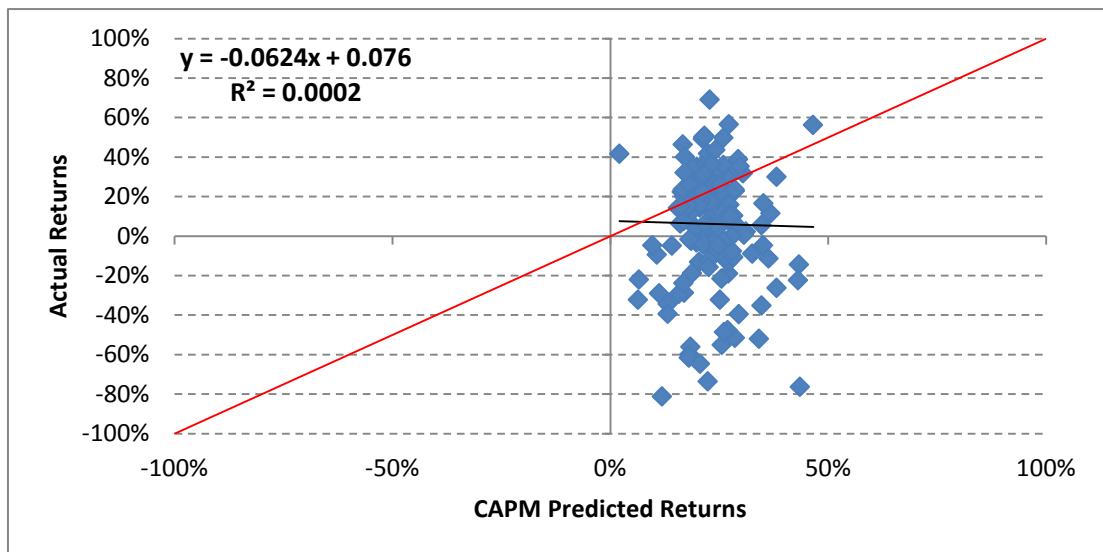
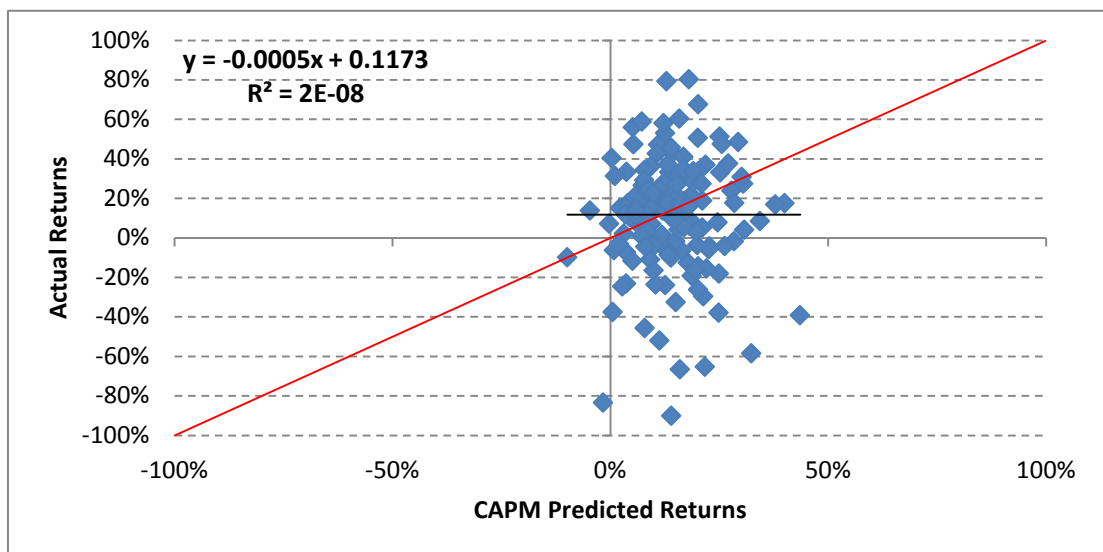


Figure 84: Black's CAPM vs Actual Returns, Dimson 24 month beta, 31 Dec 2012 - 31 Dec 2014



Appendix 9 – Graphical Analysis Black’s CAPM, Dimson 60 month beta

Figure 85: Black’s CAPM vs Actual Returns, Dimson 60 month beta, 31 Dec 1989 - 31 Dec 1994

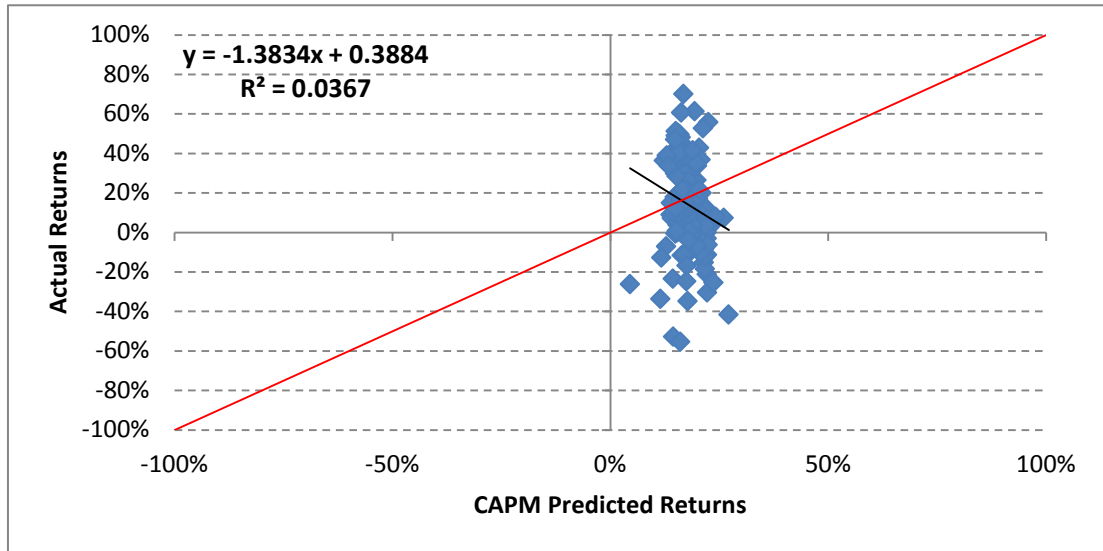


Figure 86: Black’s CAPM vs Actual Returns, Dimson 60 month beta, 31 Dec 1994 - 31 Dec 1999

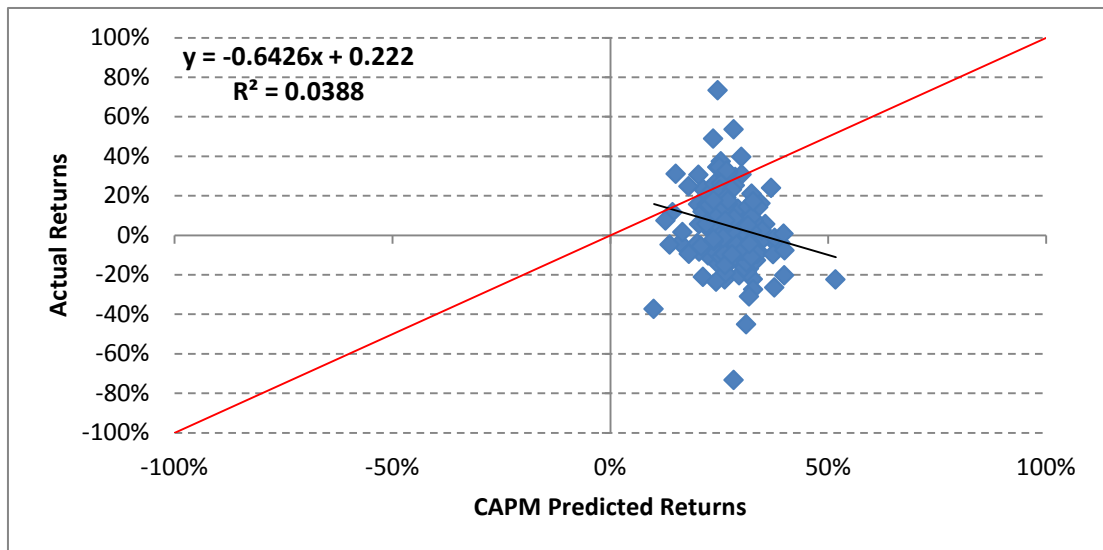


Figure 87: Black's CAPM vs Actual Returns, Dimson 60 month beta, 31 Dec 1999 - 31 Dec 2004

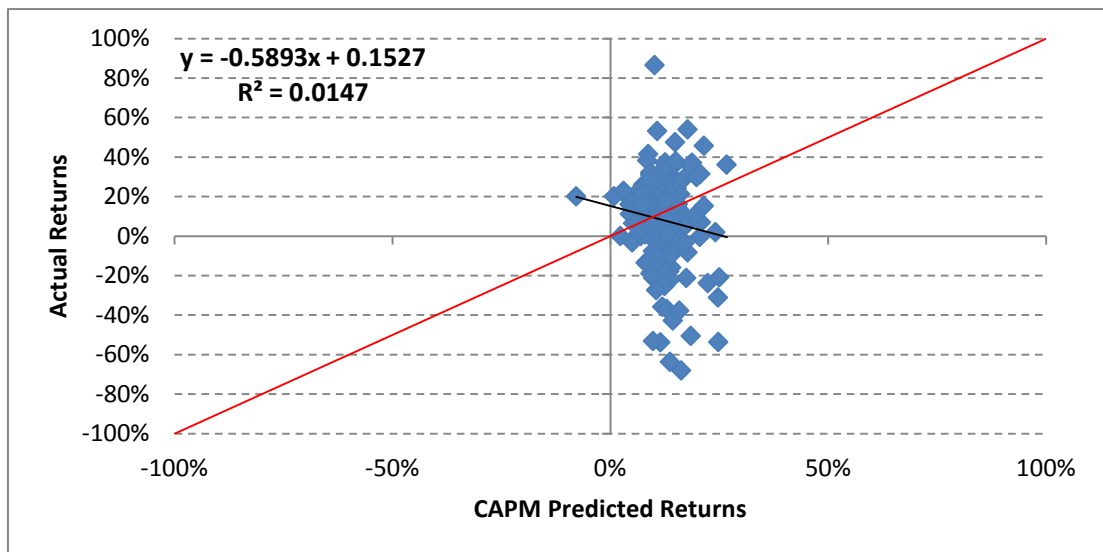


Figure 88: Black's CAPM vs Actual Returns, Dimson 60 month beta, 31 Dec 2004 - 31 Dec 2009

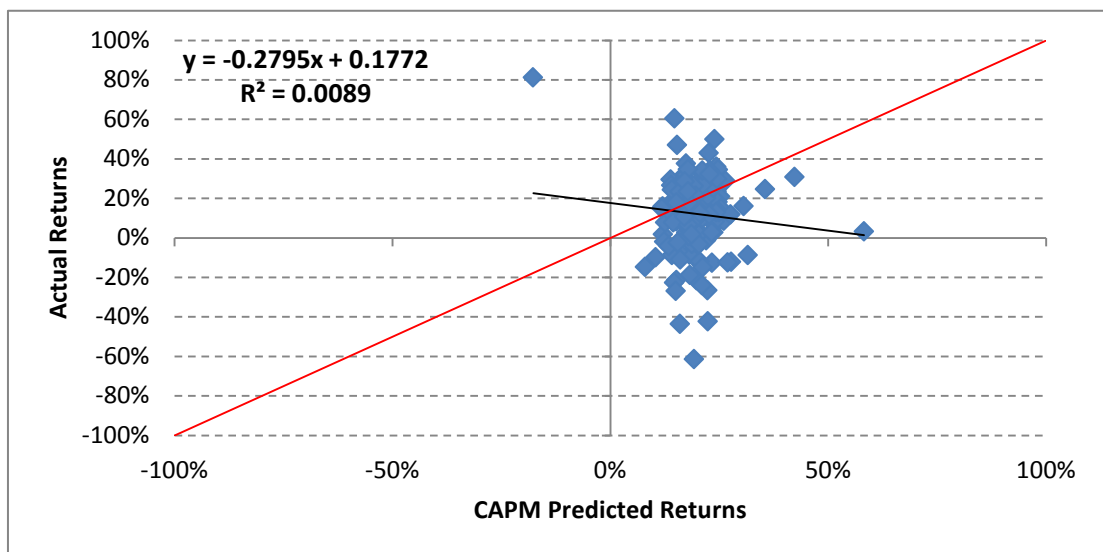
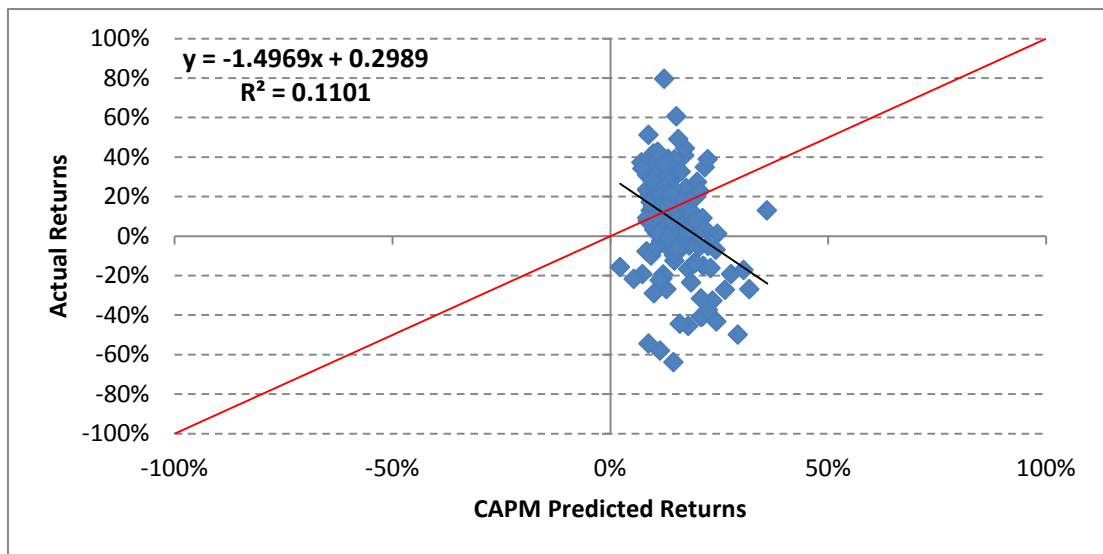


Figure 89: Black's CAPM vs Actual Returns, Dimson 60 month beta, 31 Dec 2009 - 31 Dec 2014



Appendix 10 – Ethical Clearance Letter

**Gordon Institute
of Business Science**
University of Pretoria

Dear Bradley Carter

Protocol Number: **Temp2015-00920**

Title: **Capital asset pricing model (CAPM) applicability in the South African context and alternatives**

Please be advised that your application for Ethical Clearance has been APPROVED.

You are therefore allowed to continue collecting your data.

We wish you everything of the best for the rest of the project.

Kind Regards,

Adele Bekker