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Abnormal returns on the Johannesburg Stock Exchange: Alpha as an investment style

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Abstract

While alpha is one of the most common indicators by which the performance of investment portfolios are measured little has been studied on its properties in relation to individual shares. Using the 'style engine' the study followed a portfolio based approach to evaluating alpha (as measured at share level) as an investment style on the JSE. Five equally weighted portfolios were constructed based on the alpha level displayed by shares under two different models for expected return: A JSE twelve factor model and the Fama-French five factor model. Individual portfolio performance was presented in a graphical time-series format and results were interpreted visually though the construction of price relatives as well as statistically at a significance level of 0.05.

The results showed that the effectiveness of an alpha investment style relied to a large degree on the model for expected return from which alpha was derived. Nevertheless, significant underperformance in relation to the market was observed in the lowest quintile portfolios under both models for expected return.

Keywords

Alpha, expected return, style investing, abnormal return, stock-specific

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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.

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Table of Contents

Table of Figures

List of Tables

Chapter 1: Introduction to research problem

1.1 Introduction

Strategies for achieving increased financial return are sought by investors around the world. The Investment Company Institute (2019) estimated that assets in global open-end funds (including mutual funds, hedge funds and exchange-traded funds) totalled 46.70 trillion United States (US) dollars at the end of 2018. Of this, 19.92 trillion US dollars was held in equity investments and 6.54 trillion US dollars was held in funds in Africa and Asia-Pacific. In pursuit of wealth, both institutional and individual investors, seek to beat the market expectation for return and generate abnormal returns also known as alpha. However, in the field of financial theory, the idea that it is possible to consistently generate returns that beat the market index is controversial.

The Efficient Market Hypothesis (EMH) is a good point of departure for financial theory and studies. The EMH states that security prices are an accurate reflection of all available information at the time (Fama, 1970). If the EMH holds true, then the existence of abnormal returns, or alpha, is not possible. It implies that investors have no way of beating the market or creating abnormal returns and the only way of generating increased return is through taking on additional risk. While the EMH was widely accepted by academics in the late twentieth century, by the twenty-first century there was a marked decline in the dominance of the theory (Malkiel, 2003). Most notably, Barberis and Shleifer (2003) argue that markets are not efficient and that significant profits can be made over and above returns predicted by prevailing security prices. In other words, consistently positive alpha is possible.

1.2 Models for expected return and alpha

To calculate alpha one must first define an asset pricing model for expected return. An asset pricing model is an explanatory model that seeks to explain why a share or portfolio of shares behaves the way it does. Asset pricing models typically model the expected return of an asset based on a combination of the asset's risk and exposure to one or more market related factors. Among the most popular international models are the Capital Asset Pricing Model (CAPM) (Lintner, 1965; Sharpe, 1964), the Fama-French three factor model (Fama & French, 1992), and the Fama-French five factor model (Fama & French, 2015). Alpha is defined as the deviation of an asset's return in relation to the market expectation, and in this context is equal to the y-intercept of an equation modelling expected return.

1.3 Purpose

Stock price anomalies are predictable patterns in stock price that may be exploited through an investment strategy (Meier, 2014). In the absence of an efficient market, the basis on which an investor selects stocks as well as the decision as to when to buy and sell these stocks can be termed an investment style or strategy (Keim & Madhavan, 1997). Investment strategy has been one of the most widely studied aspects of finance, and research has shown that investment styles based on stocks that display certain attributes have a tendency to outperform other stocks, as well as the market as a whole (Banz, 1981; Basu, 1977; Fama & French, 1992; Ibbotson, Chen, Kim, & Hu, 2013; Jegadeesh & Titman, 1993; Moodley, Muller, & Ward, 2016; Muller & Ward, 2013).

The question must then be posed: what investment styles might lead to outperformance over the market and what level of outperformance do these investment styles generate?

The purpose of this study will be to determine if stock selection based on alpha can be used as an investment style and how effective the style is on the Johannesburg Stock Exchange (JSE). By examining historical JSE data between 1985 and 2019 the study will seek to evaluate the feasibility of alpha as an investment style and quantify the performance associated with alpha in relation to the market.

1.4 Research objectives

Existing literature assessing investment styles has typically tested the variable of interest through the construction of equally weighted portfolios (based on variable rank) and the subsequent monitoring of the performance of these portfolios. This study ranked stocks according to alpha values derived from two models for expected return, namely the Fama-French five factor (FF5) model and a JSE twelve factor (JSE12) model. The objective of the research was to understand the relationship between alpha and return on the JSE, and to evaluate how an alpha based investment style performed in relation the market.

1.5 Theoretical need

Academically this study will add to existing literature by providing insight into the performance characteristics of stocks displaying various levels of alpha on the JSE.

One of the earliest studies into stock market anomalies was conducted by Kemmerer (1911) who investigated the effects of the seasons on the New York money market. Sixty years ago, Roberts (1959) stated that the history of stock prices was among the most intensely studied areas of economics. He argued that many believed that the market contained patterns that could provide insight into the future, if these patterns could be understood. Modern portfolio theory, a mathematical framework for constructing a portfolio of assets, similarly has a long history dating back to Markowitz (1952) and Roy (1952). Since then hundreds of studies have examined the cross-section of expected return (Harvey, Liu, & Zhu, 2016) in an effort to understand financial market behaviour. The long history and richness of the field shows the importance of theoretical understanding in financial markets.

While internationally alpha is one of the most common indicators by which investment performance is measured (Berk & van Binsbergen, 2015), literature on its properties as an investment style is scarce. Existing literature is recent (Chong, He, Ip, & Siu, 2017; Hühn & Scholz, 2018) but evaluations have only been conducted in the developed markets of the US and Europe. This study seeks to extend the body of current literature on alpha and its properties as an investment style in the emerging market context of South Africa.

1.6 Business need

Much research has highlighted the importance of the link between financial development and economic growth, both globally (Beck & Levine, 2004; Levine & Zervos, 1998) and in emerging African economies (Solarin & Dahalan, 2014). On the back of this link, the financial services industry has grown at a rapid rate over the past few decades, making the modern day mutual fund industry one of the most successful recent financial innovations (Khorana, Servaes, & Tufano, 2005). The South African collective investment industry was estimated at a value of R 2.38 trillion in March 2019 (ASISA, 2019). Clearly, research into factors that improve the performance of the mutual fund and collective investment industry has significant potential to contribute to economic growth.

There is a wide belief that institutional investors base their portfolio construction and patterns of trade on some underlying style element (Froot & Teo, 2008). Further, the prevalence and importance of certain styles (such as small capitalisation, growth, value or momentum) warrant the creation of specific mandates and underpin asset allocations for many investors and investment funds (Froot & Teo, 2008). With the advances in modern information technology, accessibility to stock markets and the ability to buy and sell shares is greater than ever before, and no longer restricted to large institutional organisations. This has given rise to a growing number of private investors who look to make a living trading stocks, often on a daily basis (Andersson, 2004). Any improvement in the understanding of financial markets and investment strategies has the potential to benefit both individual and institutional investors.

Clearly, there is a need for the advanced understanding of stock behaviour in financial markets as well as the characteristics that drive such behaviour. In a business context, this study will provide valuable insight to individual and institutional investors in South Africa. Strong performance of alpha as an investment style would provide cause for its incorporation into mutual fund or unit trust strategies, while strong underperformance would provide cause for avoidance in such strategies. Strong underperformance would also point to alpha being a useful indicator for short selling strategies that are incorporated into hedge funds. At the level of the individual investor, an evaluation of the benefits or otherwise of an alpha investment style could have a significant positive impact on the strategy and success of the investor.

1.7 Scope of research

The data set that was evaluated was limited to the 160 largest companies listed on the Johannesburg Stock Exchange by market capitalisation. Given the limited amount of time and resources available the investigation of the variable, alpha, was limited to two models for expected return. The available data set ranged from 1985 to 2019 and it was this range that the study investigated. Share price and dividend pay-outs were used as indicators of financial performance in observing the performance of quintile share portfolios. Shares' alpha values, derived from an appropriate expected return model, were used to determine the assignment of shares to the quintile portfolios.

1.8 Structure of the research report

The research report is laid out as follows:

- Chapter 2 reviews the relevant literature and theory base.
- Chapter 3 states the research hypotheses to be tested.
- Chapter 4 details the research design and methodology used to test the hypotheses.
- Chapter 5 presents the results of the research.
- Chapter 6 discusses the results of the research.
- Chapter 7 summarises the findings of the research and provides recommendations for further research.

Chapter 2: Literature Review

2.1 Introduction

Alpha is a common metric used in the evaluation of investment performance and quantifies the level of deviation of an asset's return in relation to the market expectation. Alpha may therefore be positive if a stock outperforms its expectation or negative if it underperforms its expectation. The literature review that follows outlines some of the financial theory relating to markets and the way assets are priced in these markets, market behaviour and the presence of market anomalies. It examines the concept of investment styles, the implications that these styles have for traditional concepts of asset pricing, and the potential that various styles have to deliver higher returns than the market index both internationally and on the JSE. The review concludes with an evaluation of alpha as an investment style that has the potential to deliver significantly better returns than the market index.

2.2 Market efficiency

Market efficiency is one of the key concepts of financial theory (Dimson & Mussavian, 1998). It is concerned with the degree to which market prices fully reflect all available information at a point in time, and is the assumption on which theories of expected return are based (Fama, 1970). Three forms of market efficiency have been proposed (Fama, 1970):

i. Weak-form efficiency

All historical information is reflected in stock prices and future stock prices cannot be predicted based on past performance. The implication is that technical analysis cannot produce abnormal returns, but fundamental analysis may lead to abnormal returns.

ii. Semi-strong-form efficiency

All publicly available information is reflected in stock prices and prices will change rapidly and without bias to incorporate any new information released. The implication is that technical and fundamental analysis cannot produce abnormal returns. Only information not available to the public (insider trading) may lead to abnormal returns.

iii. Strong-form efficiency

All publicly available information, all new information and all private information regarding assets is reflected in stock prices. The implication is that the generation of abnormal returns is not possible.

The EMH assumes that all publicly available information pertaining to markets is efficiently digested and reflected immediately in stock prices. The result is that stocks always trade at fair value. It is thus theoretically impossible for investors to purchase undervalued stocks or to sell stocks at inflated prices and the consistent generation of abnormal returns, or alpha, is not possible (Fama, 1998). However in the twenty-first century more economists are starting to believe that future stock prices are, at least in part, predictable based on historical price patterns and other valuation metrics (Malkiel, 2003) and that markets are not entirely efficient.

There is a long history of research that questions the efficiency of markets and the validity of the EMH. Basu (1977) showed that information related to price-to-earnings (P/E) ratios was not fully reflected in stock prices and was inconsistent with the EMH, while Banz (1981) showed that small cap stocks consistently outperformed large cap stocks on the New York Stock Exchange (NYSE). Ball (1978) provided evidence that there were significant abnormal returns on stocks after public announcements of firms' earnings, while Jegadeesh and Titman (1993) showed that investment strategies based on momentum produced significant abnormal returns. Bernard and Thomas (1990) challenged the notion that stock prices fully reflect the implications of current earnings for future earnings, because stock prices are influenced by naïve earnings expectations, while Pettit and Venkatesh (1995) found different levels of insider trading to be an indicator that successfully anticipated periods of abnormal stock returns.

In South Africa, Hoffman (2012) evaluated stock return anomalies on the JSE and concluded that certain variables could in fact be used to construct portfolios capable of generating abnormal returns. Further, the presence of these abnormal returns persisted even after adjustment for risk and Hoffman (2012) concluded that this provided strong evidence that the EMH should not be accepted.

In the absence of efficient markets, a case may be made for style investing, whereby investors are capable of exploiting patterns in stock market prices through various investment strategies. Before investigating the ways in which returns deviate from their predicted value, it is necessary to outline some of the ways in which assets are priced, since it is the model for expected return from which alpha is derived.

2.3 Asset pricing and expected return

Asset pricing models are useful in predicting the expected return of an asset and can be traced back as far as 1738 (Dimson & Mussavian, 1999). With the popularisation of complex financial instruments such as futures, forwards, warrants and options, it became increasingly important to have a means to predict the behaviour and future price of assets (Dimson & Mussavian, 1999). Research into asset pricing and expected return has been dominated internationally by the works of several authors discussed below.

2.3.1. Capital Asset Pricing Model

Early work by Sharpe (1964) and Lintner (1965), in the formulation of the CAPM, proposed that the expected return of an asset was related to the assets Beta (β), a measure of risk, as well as the risk-free rate of return. The theme of risk is central to asset pricing theory, with theory built on the premise that the risk premium of an asset is related to a measure of its systemic risk (Barillas & Shanken, 2018). The theory followed that investors would require increased financial reward in compensation for taking on additional risk. The CAPM is generally acknowledged as the origin of asset pricing theory (Fama & French, 2004) and is captured by the equation:

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

In which:	$E(R_i)$	=	the expected return of security i
	R_f	=	the risk free rate of return
	β_i	=	the beta value of security i
	$E(R_m)$	=	the expected return of the market

2.3.2. Fama-French three factor model

In light of the success of style-based approaches to investing, Fama and French (1992) suggested that the CAPM alone did not sufficiently describe historical average stock returns. Two additional factors (associated with style investing) were proposed as additions to the CAPM which, their research had shown, played a significant role in the explanation of stock returns. These factors included an adjustment for market capitalisation and book-to-market (B/M) ratio. The Fama-French three factor model (Fama & French, 1992) was proposed as an improvement on the CAPM and is captured by the equation:

$$E(R_i) = R_f + \alpha_i + \beta_i [E(R_m) - R_f] + s_i SMB + h_i HML$$

Where:	SMB	=	the return spread on capitalisation (small minus big)
	HML	=	the return spread on value (high minus low)
	α_i	=	alpha or the abnormal return
	s_i,h_i	=	factor coefficients

While the Fama-French three factor model was generally accepted in the 1990's to explain the cross-section of expected returns, it subsequently became evident that the model did not explain many of the anomalies observed in asset prices (Hou, Xue, & Zhang, 2015).

2.3.3. Carhart four factor model

In examining the persistence of returns in mutual funds, Carhart (1997) found momentum played an important role in explaining mutual fund returns. Carhart (1997) added a 12 month momentum factor to the Fama-French three factor model to form the Carhart four factor model captured by the equation:

$$E(R_i) = R_f + \alpha_i + \beta_i [E(R_m) - R_f] + s_i SMB + h_i HML + u_i UMD$$

Where:	UMD	=	the return spread on momentum (up minus down)
	u_i	=	factor coefficient

2.3.4. Fama-French five factor model

Research by Novy-Marx (2013) suggested that more profitable firms tended to provide better returns than less profitable firms. The author argued that this added an additional dimension to the value premium (HML), which had previously attributed high value stock returns to low profitability (Novy-Marx, 2013). At the same time Aharoni, Grundy and Zeng (2013) provided empirical evidence of a negative relationship between expected investment and return when investment was measured at a firm level as opposed to a share level. This led to the addition of profitability and investment as further factors to create the Fama-French five factor model (Fama & French, 2015). This model is captured by the equation:

$$E(R_i) = R_f + \alpha_i + \beta_i [E(R_m) - R_f] + s_i\,SMB + h_i\,HML + r_i\,RMW + c_i\,CMA$$

Where:	RMW	=	the return spread on profitability (robust minus weak)
	CMA	=	the return spread on investment (conservative minus aggressive)
	r_i, c_i	=	factor coefficients

2.3.5. Local models: JSE twelve factor model

Globally it has been observed that different markets display different types of market anomalies and the applicability of different market attributes may vary by region (Guo, Zhang, Zhang, & Zhang, 2017). Griffin (2002) demonstrated that local factor models explain much more of the variation in returns and generally have lower average pricing errors than any generalised world factor model. Similarly Fama and French (2012) indicated that global models did not perform well when explaining regional returns. Cakici, Fabozzi and Tan (2013) provided evidence of the need to separate emerging and developed markets when pricing assets, because the factors used to explain returns are significantly different in emerging markets compared with developed markets. The authors further showed evidence of a significant value effect on large and small stocks in all 18 emerging markets studied (Cakici et al., 2013). Hanauer and Linhart (2015) also provided evidence that global asset pricing models performed poorly for emerging markets and pricing in emerging markets did not seem to be globally integrated.

In light of the above one needs to consider the emerging market of South Africa and the JSE. Locally on the JSE, resource stocks had been found to exhibit different characteristics to other stocks in relation to expected returns (van Rensburg & Robertson, 2003). This led to the creation of a twelve factor asset pricing model for expected returns on the JSE (Ward & Muller, 2010) captured by the equation:

$$E(R_i) = \alpha_{i\,+} + \beta_{i,1}SGN + \beta_{i,2}\,SGR + \beta_{i,3}\,SVN + \beta_{i,4}\,SVR + \beta_{i,5}\,MGN + \beta_{i,6}\,MGR + \beta_{i,7}\,MVN + \beta_{i,8}\,MVR + \beta_{i,9}\,LGN + \beta_{i,10}\,LGR + \beta_{i,11}\,LVN + \beta_{i,12}\,LVR$$

Where: $\beta_{i,1} \ldots \beta_{i,12}$ = factor coefficients

$SGN_t \ldots LVR_t$ = log-function share price factors

The JSE twelve factor (JSE12) model captures the factors of:

1. Size [small, medium, large]
2. Value / Growth [low P/E, high P/E]
3. Resource / Non-Resource [resources, non-resources]

on the JSE (Ward & Muller, 2010). A detailed explanation on these parameters and the calculation thereof is provided in section 4.7.3.

2.3.6. Summary: Asset pricing models

While asset pricing models may be useful for predicting return and quantifying systemic risks for which investors seek compensation, no model is capable of being perfectly correct (Stambaugh & Yuan, 2016). Daniel and Titman (1997) pointed out that when expected returns exhibited excessive mispricing, a degree of the mispricing may be specific to the asset itself rather than the underlying factors of the model. Ultimately, whichever model is used to predict asset prices, an investment manager is required to make a selection of stocks in which to invest with the goal of increasing value for investors. In the following section different styles of investing and the factors that might influence investment choice are discussed.

2.4 Style investing and stock returns

The premise behind style investing is that assets can be classified into groups based on certain characteristics or attributes (e.g. large cap, value, bonds), and that the presence of one of these characteristics, or a combination thereof, is correlated with superior performance (Barberis & Shleifer, 2003). Investment funds are allocated to the groups rather than to individual assets. The categorisation and grouping of assets by characteristics simplifies the process of choice when faced with a large variety of different options (Mullainathan, 2002). Further the generalisation of assets into classes allows for the creation of benchmarks, enabling investors to evaluate fund manager performance among a mix of different assets (Sharpe, 1992). The attributes of these so-called styles form the basis of many of the models explaining the cross-section of expected returns. Barberis and Shleifer (2003) add that the popularity among different investment styles is often cyclic and driven by fundamental news. Thus, new styles are popularised on the back of positive news related to assets within that style and ultimately collapse when the news turns negative. Investment styles have been the topic of much research as fund managers and investors continually search for strategies to outperform the market.

Two of the most well know active investment styles are that of value investing and growth investing (Sharpe, 1978). Growth investing is underpinned by the belief that, in the long run, companies that have shown better than average gains in earnings in recent years or have high growth prospects will provide increased returns to investors (Capaul, Rowley, & Sharpe, 1993). Value investing, on the other hand, seeks to maximise returns through the selection of assets that appear ‘cheap’ in relation to other assets, i.e. they appear to have fallen out of favour but still have good fundamentals. The identification of these ‘cheap’ assets may be derived from financial and accounting ratios such as B/M value or P/E ratio (Chan & Lakonishok, 2004). There are multiple other investment styles that focus on one or more of the features of stocks and stock markets. Evidence of the effectiveness of such styles is discussed below.

2.4.1 International evidence

Value and Size: Internationally, Basu (1977) showed that securities with lower P/E ratios generally outperformed securities with higher P/E ratios. A low P/E ratio could be indicative that a stock is under-valued and that the market price is low in relation to company earnings. Banz (1981) found evidence that on average smaller firms on the New York Stock Exchange (NYSE) performed better than large firms, even after adjusting for risk. However, identifying investment value is not as simple as selecting small cap over large cap, or low P/E over high P/E. Fama and French (1992) proposed that because all style variables reflect some degree of scaling of the security price, several of the variables that impact on stock prices would be redundant in explaining average security returns. After analysing 27 years of US stock market data, between 1963 and 1990, the authors found that the cross-sectional stock returns associated with P/E, size, B/M value and leverage were captured by just two of these variables: size and B/M value (Fama & French, 1992).

Momentum: Seminal work by Jegadeesh and Titman (1993) found that a momentum style that involved buying securities that had performed well and selling securities that had performed badly over a six month time horizon showed substantial abnormal returns in US markets over the period 1965 to 1989. Subsequently, the persistence of the momentum effect has been documented on stock exchanges around the world, including European markets (Rouwenhorst, 1998) and the emerging markets of Asia, Latin America and Eastern Europe (Cakici et al., 2013). Globally, the momentum effect has been observed as one of the most significant and persistent investment styles (Jegadeesh & Titman, 2001).

Liquidity: Yan (2008) documented the importance of liquidity in relation to fund performance. Using both market capitalisation and the buy-sell spread as indicators of liquidity, Yan (2008) found evidence of a significant inverse relationship between fund size and fund performance. Ibbotson, Chen, Kim and Hu (2013) have argued that liquidity as an investment style should be given equal consideration among the most popular styles of value, size and momentum.

Volatility: Volatility (indicated by beta values), which measures systematic market risk has also been the subject of interest with regard to providing a useful investment style. Low beta values are indicative of reduced volatility and risk and are associated with lower expected returns under the CAPM. The opposite is true of high beta values. Baker, Bradley and Wurgler (2011) questioned the notion that investors taking on increased risk are compensated with increased return. In analysing US stock market data between 1968 and 2008, it was found that low volatility and low beta stocks consistently outperformed high volatility and high beta stocks. These findings where echoed in both emerging and developed markets outside of North America (Dutt & Humphery-Jenner, 2013).

Profitability: Novy-Marx (2013) suggested that profitable firms (in terms of revenues minus cost of goods sold) generated significantly higher returns than unprofitable firms, despite having significantly higher valuation ratios. He showed that most earnings-related anomalies were explained by controlling for profitability while significantly increasing the performance of value based investment strategies. Fama and French (2006) also found that taking profitability and investment into account, firms with higher B/M equity displayed higher expected stock returns. Thus, it would be of benefit to incorporate gross profitability as a meaningful style in any investment strategy.

2.4.2 Evidence on the JSE

The issue of investment style in relation to stock returns has also been the subject of much investigation on the JSE. In the introduction to their paper discussing style-based effects on the JSE, Muller and Ward (2013) provide an excellent review of the research into various style-based strategies for investment on the JSE. Some of the more significant analyses are briefly described below.

A study by van Rensburg (2001) examined more than 20 different factors, with the aim of identifying the style factors that explained the expected returns of the JSE industrial sector. The study found eleven persistent CAPM anomalies present on the JSE that could be consolidated into three groups through cluster analyses: value, quality and momentum.

Bhana (2007) showed that an investment style that followed open market share repurchase announcements showed significant outperformance in the three-year period following the announcement. The effect was found to be most pronounced when applied to value stocks. More recently, Wesson, Muller and Ward (2014) echoed these findings. In addition, Bhana (2008) found evidence of significant excess returns to be made in following capital expenditure announcements on the JSE between 1995 and 2004.

Mutooni and Muller (2007) determined that value stocks outperformed growth stocks across the entire size spectrum on the JSE. The authors also expanded the idea of style investing by looking beyond the asset characteristics in which to invest and focusing on timing strategies related to when to invest. The authors found evidence that style timing was capable of further improving the returns that investors could make.

Strugnell, Gilbert and Kruger (2011) examined the cross-section of returns on the JSE between 1994 and 2007 and found significant evidence of the size and value effect on the JSE as well as evidence of a negative relationship between beta and return. The negative relationship with beta is of particular interest as it contradicts the CAPM. Strugnell et al. (2011) concluded that beta is irrelevant in relation to return on the JSE and it is unable to explain the observed returns on the JSE. Similar findings were reported by Ward and Muller (2012) who observed the same inverse relationship between beta and return on the JSE between 1987 and 2000. These findings, specific to the JSE, were in line with the international findings of Baker et al. (2011) who found low volatility and low beta stocks consistently outperformed high volatility and high beta stocks on US markets.

Hoffman (2012) conducted a study into seven parameters and their ability forecast return anomalies on the JSE between 1985 and 2010. These parameters included market capitalisation, B/M ratio, net share issues, yield-to-book ratio, accruals, change in assets and 12 month price momentum. The results provided further evidence against the EMH, proving that certain variables could, in fact, be used in constructing portfolios that would consistently produce abnormal returns. The most prevalent variables were found to be market capitalisation, B/M ratio and 12 month price momentum.

In one of the most comprehensive style studies on the JSE, Muller and Ward (2013) examined the performance of 11 different investment styles using data from 1985 to 2011. Muller and Ward (2013) showed that momentum was the most prevalent style, outperforming the JSE All Share Index (ALSI) by 8.9% annually. Muller and Ward (2013) also showed that persistent annual outperformance of up to 14% could be achieved over the JSE ALSI by employing a combination style that included return-on-capital, cash flow to price and earnings yield in addition to momentum. In contrast to other studies the analyses indicated no relationship between size and returns.

Moodley, Muller and Ward (2016) found statistically significant evidence that an investment style that followed JSE director trades on the buy side outperformed the market by 4.6% per annum between 2002 and 2005. It must be noted, however, that evidence of the effectiveness of this style was not present between 2006 and 2013.

2.5 Alpha and stock-specific factors

2.5.1 Alpha

Barillas and Shanken (2017) define classic investment alpha as “the intercept in the time-series regression of an asset’s excess returns on those of the market portfolio” (p.1316). Simply put it is the deviation of an asset’s return in relation to the market expectation, and is equal to the y-intercept of an equation modelling an asset’s expected return against the return of the market index. Alpha is thus that element of expected return which cannot be explained by an asset pricing model and it follows that the better the model for expected return the closer alpha will be to zero.

Early work by Jensen (1968) recognised the need for an alpha term in models of expected return in order to measure the performance of asset managers. By not constraining the CAPM to pass through the origin, Jensen (1968) argued that an allowance was made for the superior forecasting ability of asset managers. The CAPM equation could thus be defined by:

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

Managers capable of investing in stocks whose prices beat the market would be said to generate positive alpha (Jensen, 1968) over a benchmark index. Over the years, the extension of the CAPM to include additional market factors (such as SMB, HML and CMA) generated increasingly complex asset pricing models that better explained the cross-section of expected returns. The y-intercept of any asset pricing model that includes such factors can still be interpreted as an asset's deviation from its expected return model or alpha. Clearly, the calculation of alpha is related to the asset pricing model itself and may vary depending on the model employed. While many studies have used the presence of alpha as a measurement of investment strategy or manager effectiveness, there has been little investigation on the use of the variable itself as an investment strategy.

2.5.2 Stock-specific factors

In examining the cross-section of stock returns under the Fama-French three factor model, Fama and French (1993) noted that while the factors did a good job of explaining the cross-section of expected returns, the y-intercept was still non-negative and higher than 0.20% per month in over 12% of cases tested. Similarly, results from the Fama-French five factor model found evidence that certain stock groups (in particular small stocks with low profitability) fared poorly under the model, displaying average unexplained returns of 0.34% per month (Fama & French, 2015). Daniel and Titman (1997) pointed out that when expected returns exhibited excessive mispricing, a degree of the mispricing may be specific to the asset itself rather than the underlying factors of the model. Black (1993) made the case that asset pricing theory simply explained return and pricing variance rather than actually estimating it. The author added that models for expected return, which all rely on factors to some degree, rely heavily on data and not enough on theory. In formulating models for expected return, Black (1993) suggested that the authors (such as Fama, French and Carhart) incorporated factors into their models believing that these factors represented risks that investors cared about. Yet, when assets behaved differently from these models, investors used terms such as mispriced or irrationally priced to explain these variations from the models (Black, 1993). Black (1993) argued that this was because investor psychology played a large role in observed returns, changing dynamically with time as short term fads entered and exited the investment market.

In the CAPM, Fama-French and Cahart pricing models, the alpha term is used to explain abnormal or excess return that is not attributable to fixed factors such as SMB, HML and CMA. While 95% of return variability may be explained by factor models (Grundy & Martin, 2001), there is an element of return variability that cannot be attributed to common linear factors across the market. Grundy and Martin (2001) thus defined stock-specific returns as those components of return that are not ascribable to the factors of expected return models. On this basis, alpha may be thought of as idiosyncratic in nature and directly related to the asset in question (Pontiff, 2006).

2.5.3 Stock-specific and alpha based studies

In assessing the profitability of momentum based strategies, Grundy and Martin (2001) argued that the momentum must be reflected in some component of the stock return that was not taken into account by the risk adjustment offered by market and size factors. Grundy and Martin (2001) added that the profitability associated with such a strategy must have been derived from exposure to components of stock return that were not associated with the calculation of the risk adjustment factors, such as beta, SMB and HML. Their stock-specific momentum strategy bought winners and sold losers based on stock-specific alpha estimates for stocks on the NYSE and American Stock Exchange (AMEX). The result strongly suggested additional profits could be realised by following such a stock-specific strategy after breaking down total returns into factor components and stock-specific components. The existence and effectiveness of stock-specific idiosyncratic momentum has also been documented by Gutierrez and Prinsky (2007) as well as Blitz, Huij and Martens (2011).

Stambaugh and Yuan (2016) investigated the prevalence of abnormal returns with regard to factor models. The authors argued that while many studies observed the presence of anomalies that violate asset pricing models, very seldom were such anomalies considered for incorporation as additional factors to pricing models (Stambaugh & Yuan, 2016). This was likely due to the absence of persistence in the driver of a single anomaly. Stambaugh and Yuan (2016) took the approach of combining the information related to 11 anomalies identified in literature into a single factor, as opposed to incorporating an additional factor term for each anomaly variable. The approach allowed a wide range of anomalies to be incorporated by averaging the rankings across many anomalies. Stambaugh and Yuan (2016) argued that the averaging achieved a less noisy measure of stock mispricing. Their approach treated each stock's averaged anomalous return as a proxy term for alpha. This term was then added to market and size factors to create a four factor mispricing factor model. The authors evaluated this model on US stock exchanges using data between January 1967 and December 2013. The four factor mispricing factor model outperformed both the Fama-French five factor model and an alternate four factor model put forward by Hou et al. (2015), suggesting that a multitude of anomalies may be captured by a single factor.

Chong et al. (2017) highlighted that the lack of risk adjustment was a possible cause for the mixed evidence in relation to the drivers of momentum profits, in many of the momentum based studies conducted. The authors argued that momentum based profits were better measured after adjusting for both firm and market based risk. The reasoning behind this was that historical stock returns may have contained risk elements that continued to affect the stock performance into the future (Jegadeesh & Titman, 1993). Chong et al. (2017) employed a risk adjusted momentum strategy on US stock markets between 1964 and 2013, buying winners and selling losers according to alpha estimates from the CAPM and Fama-French three factor model. After the exclusion of small and illiquid stocks, alpha estimates ranged from -1.61% to 12.48% under CAPM calculation and from -1.90% to 13.22% under Fama-French three factor model calculation (Chong et al., 2017). Ten equally weighted portfolios were constructed according to descending values of the previous six months (i) CAPM alpha and (ii) Fama-French three factor model alpha. Their results indicated the existence of alpha as a style, with portfolios constructed from high alpha stocks consistently outperforming portfolios constructed from low alpha stocks. In addition it was shown that improved Sharpe ratios could be obtained through the construction of a market neutral portfolio based on alpha (Chong et al., 2017).

Hühn and Scholz (2018) found alpha to be both economically and statistically significant in predicting the cross-section of stock returns in Europe between 1987 and 2014 and in the US between 1981 and 2014. Using a similar methodology to Grundy and Martin (2001), Hühn and Scholz (2018) ranked stocks according to stock-specific alpha estimates derived from the Fama-French three factor model. However, unlike Grundy and Martin (2001) the authors' alpha estimates were calculated considering daily stock returns and by calculating factor regression parameters during the formation period only. This eliminated the possibility of factor exposures before the formation period from impacting their rankings (Hühn & Scholz, 2018). In a similar manner to Chong et al. (2017), ten equally weighted portfolios were constructed and evaluated according to descending values of alpha. Their results found alpha to be a statistically significant predictor of cross-sectional returns in the US and Europe. In addition, alpha momentum displayed superior returns and higher Sharpe ratios than traditional price momentum in US, but inferior returns in Europe when compared to price momentum (Hühn & Scholz, 2018).

2.6 Conclusion

The literature shows that the popularity and success of various investment styles on global stock exchanges cast doubt on the validity of efficient market theories such as the EMH. There are several factors that impact on stock prices that have led to style investing. The literature indicates that international and South African stock portfolios that are constructed according to certain style variables such as momentum, return on capital, size, profitability and earnings yield can, on average, perform better than the market. While much work has been done on the improvement of models of expected return, alpha persists as an anomaly on stock exchanges throughout the world. No model for expected return is perfect and some degree of stock-specific alpha is present in all models. The idiosyncratic nature of alpha, along with the success of other stock-specific and style-based investment strategies, gives cause for its investigation as an investment style on the JSE.

Chapter 3: Research Hypotheses

The literature review in Chapter 2 outlined a number of asset pricing models. These models ranged from the original one factor CAPM to the FF5 model and a twelve factor model for estimating returns on the JSE. It was also noted that none of these increasingly sophisticated asset pricing models managed to fully capture expected returns, and anomalies between expected returns and actual returns persisted. This led to the research of alpha as an investment style. The literature review indicated that portfolios constructed from high alpha stocks appeared to outperform portfolios constructed from low alpha stocks. However, there has been little study of alpha as an investment style on the South African stock market. The research undertaken in this study aimed to investigate whether a stock's alpha value could be used as an investment style in the South African context, and if so, how effective this investment style was in comparison to the market.

For the purposes of analysis, two asset pricing models were investigated using portfolios constructed of stocks with varying alpha values: the models were the JSE12 model and the FF5 model and the following three hypotheses were investigated.

3.1 Hypothesis 1

$H1_0 : P1 \leq P2 \leq P3 \leq P4 \leq P5$

$H1_a : P1 > P2 > P3 > P4 > P5$

Where P1 represents the portfolio constructed from the highest alpha value shares and P5 represents the portfolio constructed from the lowest alpha value shares.

The null hypothesis states that portfolios constructed from higher alpha value shares perform equally to, or worse than, portfolios constructed from lower alpha value shares over the period of evaluation. The alternate hypothesis states that portfolios constructed from higher alpha value shares perform better than portfolios constructed from lower alpha value shares over the period of evaluation.

3.2 Hypothesis 2

$H2_0$: P1 ≤ JSE ALSI

$H2_a$: P1 > JSE ALSI

The null hypothesis states that a portfolio constructed from the highest alpha value shares (P1) underperforms or performs equally to the market. The alternate hypothesis states that a portfolio constructed from the highest alpha value shares outperforms the market. The market is represented by the JSE ALSI.

3.3 Hypothesis 3

$H3_0$: P5 ≥ JSE ALSI

$H3_a$: P5 < JSE ALSI

The null hypothesis states that a portfolio constructed from the lowest alpha value shares (P5) outperforms or performs equally to the market. The alternate hypothesis states that a portfolio constructed from the lowest alpha value shares underperforms the market. The market is represented by the JSE ALSI.

Chapter 4: Research Methodology

4.1 Choice of Methodology

An independent and objective quantitative study was conducted using secondary financial data from shares listed on the JSE. The results of the study were intended to be free from human bias and suitable for statistical analysis. The underlying philosophy of the study was positivist since it was based on quantitative research methodologies and the use of statistical analyses (Mukherji & Albon, 2014).

A deductive study incorporates developing testable hypotheses, the collection of quantitative data and the analysis of the collected data to test the truth or falsity of the hypotheses (Saunders & Lewis, 2018). The systematic, step-wise approach to answering the research hypotheses through the construction of test portfolios, and the subsequent quantitative analysis of portfolio performance based on financial data, lent itself to a mono-method deductive study.

The research strategy explored the existence of a causal link between two variables: the alpha value of a share and its performance on the stock market. In a true experiment, random selection and subsequent assignment to a control group is required (Bhattacherjee, 2012). As control groups in this study were assigned according to pre-determined characteristics the approach became quasi-experimental. Bhattacherjee (2012) highlights that while inferences drawn from laboratory-based true experiments are more robust in internal validity, a quasi-experimental approach is more robust in external validity and more suitable to field experiments based on real life data.

The research employed a time-series evaluation of observed share returns between 1 January 1985 and 31 May 2019. The level of the independent variable, alpha, was quantified quarterly over the duration of the study according to historic secondary data. A detailed description of this process is provided in section 4.7.

4.2 Population

Saunders and Lewis (2018) define a population as the complete set of group members. In this case the group members were listed shares on the JSE. JSE Limited regulates South Africa's primary and secondary markets including all information services and market data. The existence of such data meant that all 374 companies listed on the JSE could potentially have been included in the population.

Muller and Ward (2013) have noted that although there are over 350 companies listed on the JSE, the JSE ALSI is made up of the largest 160 of these companies and comprises about 99% of the total market capitalisation of the JSE. Further, the illiquid nature of the smallest 1% of the JSE is of little interest to institutional investors (Muller & Ward, 2013) and would prove difficult to rebalance frequently. Thus, listed shares falling outside the JSE ALSI were excluded from the study on this basis, and the largest 160 companies making up the JSE ALSI between 1985 and 2019 formed the population of the study. In following the methodology of Muller and Ward (2013) newly listed shares were included in the population from the beginning of the quarter after which they listed, and delisted shares remained at their final price until the end of the current quarter, before being removed from the population.

4.3 Unit of Analysis

The unit of analysis for the graphical time-series analysis was the cumulative return of the equally weighted share portfolios. For the statistical hypotheses testing, the unit of analysis was defined as the monthly returns of each portfolio. The unit of observation was defined as share performance on the JSE over the same period. Share performance was tracked cumulatively in South African Rand (ZAR), according to the daily closing price of each share and included any dividends paid out. Portfolios were equally weighted and constructed according to descending values of the independent variable, alpha.

4.4 Sampling Method and Size

As described, the JSE ALSI is made up of the largest 160 companies on the JSE and these companies comprise 99% of the total market capitalisation of the JSE (Muller & Ward, 2013). Thus, virtually all movement in the JSE is a result of movement in shares included in the JSE ALSI data set. On this basis it was these 160 companies that formed the population and sample size of the study. The 1% of companies outside of this were not liquid enough to be considered of interest to investors and may not have been suited to frequent portfolio rebalancing. As such, the method of selection for inclusion in the data set was based on company size (by market capitalisation) and interest to investors, and this was considered to comprise a total population sample or census. The advantage of sampling the total population is that it reduces the sampling error often associated with selection bias (Thygesen & Ersbøll, 2014).

4.5 Measurement Instrument

Secondary data pertaining to the financial characteristics of shares listed on the JSE ALSI formed the basis of the measurement instrument. The population was divided into five equally weighted portfolios based on descending alpha values of individual shares. Portfolios were rebalanced quarterly based on the updated alpha values of the shares in the population.

The performance of each equally weighted portfolio was analysed in relation to the four other equally weighted portfolios. In addition, the portfolio that contained the highest (P1) and lowest (P5) value alpha shares was analysed in relation to the JSE ALSI. The results were interpreted in several ways:

4.5.1 Portfolio value

Portfolio performance was derived from the cumulative value of shares within each portfolio. Share performance was in turn derived from the daily closing price of shares on the JSE and included any dividends paid out. Portfolios were tracked from a base value of one. At the end of each quarter the value of each portfolio was retained, and the five equally weighted portfolios reconstructed according to the updated alpha values of shares within the population.

4.5.2 Visual analysis

The cumulative value of each portfolio was plotted graphically in a time-series analysis in line with Muller and Ward (2013). The graphical plot allowed for a simple and intuitive analysis of the relative performance of portfolios in relation to one another and the JSE ALSI. In addition, a graphical representation of a price relative was included, which indicated periods in which the investment style worked and periods in which it did not work.

4.5.3 Compound annual growth rate

The compound annual growth rate (CAGR) is a valuable concept that allows the comparison of different investments over varying periods of time. The CAGR gives an indication of the constant growth rate (from initial to final value) achieved over the time period and is calculated by:

$$CAGR = \left(\frac{End\ Value}{Start\ Value}\right)^{\frac{1}{No.\ Periods}} - 1$$

The CAGR provided a numerical indication of the performance of each portfolio as well as the JSE ALSI over the duration of the study.

4.5.4 Monthly return

The monthly return of each portfolio was derived from the monthly, cumulative portfolio value. These monthly return values allowed the traditional statistical tests for differences to be performed between mean portfolio returns. Log returns were used to ensure compounding was correctly taken into account.

4.6 Data Gathering Process

Secondary data is defined as any data that has been gathered by a third party and includes data that may be reused in studies for which it was not originally intended (Ribeiro & Fernando, 2018). Company financial information for JSE listed companies is available from online database platforms such as JSE, IRESS and McGregor and as such it constitutes secondary data. Available information includes:

- Opening and closing share prices
- Trading volumes
- Market capitalisations
- Price to earnings ratios
- Dividend payments

4.6.1 Style Engine

The data set to be interrogated was drawn from the ‘style engine’ that was developed and used by Muller and Ward (2013). The ‘style engine’ represents a comprehensive set of financial parameters for JSE listed companies, captured in a Microsoft Access database. ‘Style engine’ data exists from 31 December 1984 to the present, and is adjusted and complete for stock splits, name changes, listings and de-listings. Visual Basic for Applications (VBA) may be used in conjunction with Microsoft Excel to extract and manipulate the data to the needs of the user. As such, parameters including the number of portfolios to be assessed, start date, end date, ranking and holding period, may easily be changed and analysed (Muller & Ward, 2013).

The ‘style engine’ constituted the database that was assessed for the study.

In following the methodology of Muller and Ward (2013), dividends and script dividends were included in the calculated returns, while share buybacks and those granted as compensation were ignored. New share listings were included at the beginning of the subsequent portfolio rebalancing period and delisted shares were dropped at the end of the current portfolio period. Delisted shares were recorded at their final list price until the end of the period.

4.7 Analysis Approach

As indicated in the literature there are several methods for estimating the expected return of an asset, from which an alpha value may be determined, after calculating the y-intercept of the expected return equation. Internationally the most popular of these methods include:

i. CAPM
ii. Fama-French three factor model
iii. Fama-French five factor model

The study evaluated alpha as an investment style in relation to two expected return models. The resultant constant to be added to the best fit expected return equation was used as the variable, alpha. Some of the considerations that were taken into account when selecting the expected return models for the study are discussed below.

4.7.1 CAPM

The CAPM was not included as a method for alpha determination in this study. This was based on the findings of Strugnell et al. (2011), who observed an inverse relationship between beta and return (in contradiction to the CAPM) and concluded that beta was unable to explain the observed returns on the JSE. Similar findings were documented by Ward and Muller (2012), who observed an inverse relationship between beta and stock return on the JSE between 1987 and 2000 and no relationship between 2004 and 2011. This indicates that the CAPM is insufficient to explain returns on the JSE. Globally, similar studies have found evidence against the validity of the CAPM on US stock markets (Baker et al., 2011; Fama & French, 1992).

4.7.2 Fama-French five factor model

The Fama-French five factor model was selected for inclusion over the Fama-French three factor model, as it included all factors contained in the three factor model, as well as the inclusion of two additional factors: profitability and investment. Internationally, the five factor model was shown to be superior to the three factor model (Fama & French, 2015) and was found to display the better results on the JSE (du Pisanie, 2018). The model was parameterised by:

$$E(R_i) = R_f + \alpha_i + \beta_i[E(R_m) - R_f] + s_iSMB + h_iHML + r_iRMW + c_iCMA$$

where $E(R_i)$ indicated the expected return of a share, $[E(R_m) - R_f]$ the market risk premium and SMB to CMA indicated the share return on the respective factor characteristics. β_i to c_i indicated factor loading coefficients calculated from monthly log regressions. The resultant y-intercept of the best fit equation denoted alpha, α_i (see section 2.3.4).

4.7.3 JSE twelve factor model

It has been observed that different markets display different types of market anomalies and the applicability of different factors may vary by region (Guo et al., 2017). For example, on the JSE, resource stocks have been found to exhibit different characteristics to other stocks (van Rensburg & Robertson, 2003). In an attempt to ensure that results were as representative as possible, a twelve factor JSE model, as proposed by Ward and Muller (2010), was used as an expected return model for alpha. The twelve factors are based on:

1. Size [small, medium, large]
2. Value / Growth [low P/E, high P/E]
3. Resource / Non-Resource [resources, non-resources]

Market capitalisation represented the size factor. The 40 largest shares were defined as large, shares 41 to 100 were defined as medium, and the remaining shares were defined as small. The P/E ratio was used to split value from growth and shares where P/E ratios below the median were defined as value shares while shares with P/E ratios above the median were defined as growth shares. Shares were defined as resource shares based on their JSE sector classification while all shares outside of the resource sector classification were defined as non-resource shares. The twelve factors are summarised in the table below:

Table 1: Twelve style factors to model expected return on the JSE

Factor	Resource / Non-resource	Value / Growth company	Company size
SGN	Non-resource	Growth	Small
SGR	Resource	Growth	Small
SVN	Non-resource	Value	Small
SVR	Resource	Value	Small
MGN	Non-resource	Growth	Medium
MGR	Resource	Growth	Medium
MVN	Non-resource	Value	Medium
MVR	Resource	Value	Medium
LGN	Non-resource	Growth	Large
LGR	Resource	Growth	Large
LVN	Non-resource	Value	Large
LVR	Resource	Value	Large

(Ward & Muller, 2010)

The model was parameterised by:

$$E(R_i) = \alpha_{i\,+} + \beta_{i,1}SGN + \beta_{i,2}\,SGR + \beta_{i,3}\,SVN + \beta_{i,4}\,SVR + \beta_{i,5}\,MGN + \beta_{i,6}\,MGR + \beta_{i,7}\,MVN + \beta_{i,8}\,MVR + \beta_{i,9}\,LGN + \beta_{i,10}\,LGR + \beta_{i,11}\,LVN + \beta_{i,12}\,LVR$$

where $E(R_i)$ indicated the expected return of a share and SGN to LVR indicated the share return on the respective factor characteristics. $\beta_{i,1}$ to $\beta_{i,12}$ indicated the factor loading coefficients calculated from monthly log regressions. The resultant y-intercept of the best fit equation denoted alpha, α_i.

In following the methodology of Muller and Ward (2013), once the alpha term was determined from the respective expected return model, shares were ranked in descending order according to their alpha values. Shares were then split into five equally weighted portfolios. The value of each portfolio was tracked monthly from a base of one. The value of the market, represented by the JSE ALSI total return index (J203TRI), was also tracked monthly from the same base. At the end of every quarter, the value of each of the five portfolios was retained, while the alpha value of all shares was updated according to the most recent calculations. After re-ranking shares based on their updated alpha values, the five equally weighted portfolios were reconstructed.

This process was repeated for each expected return model for the duration of the study and the cumulative value of each portfolio was plotted for a visual comparison of the results. In addition, the CAGR was used to quantify the performance numerically (see section 4.5.3). Finally, two price relatives were included for each expected return model to aid graphical interpretation of the data. The first price relative plotted the highest alpha value portfolio (P1) divided by the lowest alpha value portfolio (P5), while the second price relative compared P1 to the JSE ALSI. The slope of the price relatives gave an indication of periods in which the style effects were present.

4.8 Quality Controls

4.8.1 Research Data

The integrity of the data in the 'style engine' was validated through the replication of an index, weighted by market capitalisation, from all data present in the 'style engine'. The performance of this index was then compared to the performance of the J203TRI (also a market capitalisation weighted index) over a comparable time period. A close tracking of the two indices was observed (Muller & Ward, 2013; Ward & Muller, 2012) and validated the integrity of the data present in the 'style engine'.

4.8.2 Research Methodology

The methodology was validated through the construction and testing of randomised portfolios. After creating five equally weighted portfolios based on random selection (Muller & Ward, 2013; Ward & Muller, 2012), it was observed that these portfolios tracked randomly with no clear separation between portfolios. This validated the methodology as being free from any form of inherent bias (Muller & Ward, 2013; Ward & Muller, 2012).

4.8.3 Research Results

The cumulative portfolio values, plotted in a graphical time-series approach, provided an intuitive visual means of assessment for the study. The traditional statistical tests for significance were performed to further evaluate and validate the results. All statistical tests were performed at a significance level of 0.05.

4.8.3.1 Tests for Normality

An assessment of the distribution of the data was required for statistical testing. When the assumption of normality is violated the results of certain statistical tests may not be valid or reliable (Razali & Yap, 2011). The study found all data to be non-normally distributed indicating a requirement for non-parametric statistical tests. Non-parametric tests do not rely on any assumption about the underlying distribution of the data.

4.8.3.2 Rank Tests and Ordered Alternatives

Rank based tests were used to evaluate the significance and ordered rank of the performance of the alpha based portfolios. Rank tests are non-parametric tests used to make statistical inferences about the rank of sample observations (Hajek, Sidak & Sen, 1999). Similarly to Viljoen (2016), the Jonckheere-Terpstra test for ordered alternatives was used to evaluate Hypothesis 1 based on the predicted order of portfolio performance. This was followed by a *post hoc* evaluation of the location of the differences. The Wilcoxon signed-rank test was used to compare the two means of a single sample in the evaluation of Hypothesis 2 and Hypothesis 3.

4.8.4 Bootstrapping

Mooney and Duval (1993) describe bootstrapping as a computer based statistical technique relying on resampling to accurately estimate a sample's distribution. Salkind (2010) adds that the bootstrapping technique is suitable for use in time-series analysis. The 'style engine' data was used to create 100 random bootstrap portfolios from the study population. The cumulative value and CAGR of the 100 portfolios were recorded over the duration of the study. The performances of P1 (high alpha portfolio) and P5 (low alpha portfolio) were compared to the performance of the 100 random portfolios to ascertain whether the observed performance of the alpha based portfolios could be attributed to chance.

4.9 Limitations

4.9.1 Stock Exchange

The main limitation in this study was associated with the small and very specific stock market on which the study was focused. The market capitalisation of the JSE stands at approximately 1.1 trillion US dollars, while the NYSE has a market capitalisation in the order of 30 trillion US dollars. Due to the small size of the JSE, and subsequent small size of the quintile portfolios, there is the risk that abnormal behaviour by a single share could skew the data considerably.

4.9.2 Expected Return Model

The expected return models and associated alpha variables were selected for their suitability to the JSE based on the literature reviewed. While two models were tested as part of the study, several models were not tested. Different results may have been obtained using different models to calculate expected return, and depending on the models suitability for the stock exchange evaluated. Cakici et al. (2013) highlight the need to separate developed and emerging markets when pricing assets, therefore the results obtained under different expected return models may vary on different stock exchanges around the world.

4.9.3 Frequency of Calculation

The calculation of alpha on a quarterly basis takes into account a lower number of observations than if alpha was calculated on a daily basis. Differences could therefore arise between factor exposures of shares during the quarterly formation periods (Hühn & Scholz, 2018).

4.9.4 Data Range

Finally, the study has been conducted on historic JSE data over the period January 1985 to May 2019. Results for periods and stock exchanges outside of this may exhibit different characteristics.

Chapter 5: Results

5.1 Introduction

This chapter provides an overview of the results that were obtained. Graphical representation of the cumulative portfolios values and their associated price relatives are presented, along with the results of statistical analyses that were conducted on the monthly return data.

As described in Chapter 4, two different models for the expected return and associated alpha values were tested. The results from the JSE twelve factor (JSE12) model are presented in section 5.3, and the results from the Fama-French five factor (FF5) model are presented in section 5.4. The three research hypotheses are addressed in relation to each model for expected return.

5.2 Sample statistics for the entire population

Table 2 provides the mean of the quarterly alpha values across all portfolios for both the JSE12 and FF5 models for the time period 1985-2019. Maximum and minimum values and standard deviations are also indicated.

Table 2: Quarterly alpha values

	N	Minimum Alpha	Maximum Alpha	Mean Alpha	Std. Deviation
JSE12 All Data (P1-5)	690	-3.93%	4.29%	-0.11%	1.76%
JSE12 P1	138	0.99%	4.29%	2.42%	0.65%
JSE12 P2	138	0.06%	2.82%	0.66%	0.44%
JSE12 P3	138	-0.68%	2.13%	-0.13%	0.42%
JSE12 P4	138	-1.42%	1.42%	-0.90%	0.43%
JSE12 P5	138	-3.93%	-0.39%	-2.62%	0.67%
FF5 All Data (P1-5)	690	-4.17%	5.35%	0.63%	1.90%
FF5 P1	138	1.68%	5.35%	3.18%	0.78%
FF5 P2	138	0.66%	3.26%	1.44%	0.66%
FF5 P3	138	-0.51%	2.54%	0.63%	0.72%
FF5 P4	138	-1.55%	1.91%	-0.17%	0.82%
FF5 P5	138	-4.17%	0.40%	-1.95%	1.18%

Clearly, for both asset pricing models, mean alpha values for P1>P2>P3>P4>P5, and are in line with the research design. The mean quarterly alpha value of the entire population over the period of evaluation was -0.11% under the JSE12 model and 0.63% under the FF5 model.

5.3 JSE twelve factor model

5.3.1 Hypothesis 1

Hypothesis 1 was concerned with the differences in returns among portfolios that were constructed using the alpha value of JSE listed shares as a basis for ranking the shares.

The null hypothesis stated that portfolios constructed from higher alpha value shares would perform equally to, or worse than, portfolios constructed from lower alpha value shares (where the average alpha value of shares in a portfolio decreases from P1 to P5) over the period of evaluation. The alternate hypothesis stated that portfolios constructed from higher alpha value shares would perform better than portfolios constructed from lower alpha value shares over the period of evaluation.

$H1_0$: P1 ≤ P2 ≤ P3 ≤ P4 ≤ P5
$H1_a$: P1 > P2 > P3 > P4 > P5

5.3.1.1 Descriptive statistics

As described in Chapter 4, the data set comprised all shares listed on the JSE ALSI from 1985 up to and including May 2019. JSE ALSI stocks were ranked in descending order, based on their calculated alpha values at the start of each quarter. Alpha for each stock was determined from the resultant y-intercept of the best fit equation from the JSE12 model for expected return. Figure 1 indicates the mean quarterly alpha values of the constituents of each portfolio over the period of evaluation under the JSE12 model. P1 represents shares with the highest alpha values, while P5 represents the shares with the lowest alpha values.

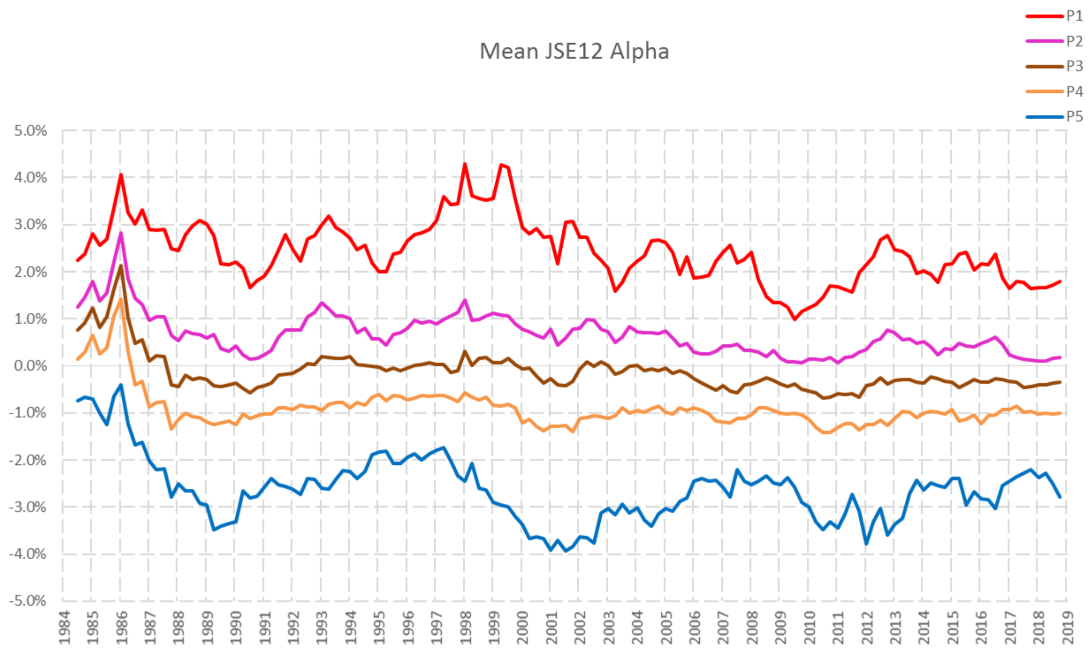

Figure 1: Mean quintile alpha values: JSE12 model

As cumulative portfolio values were tracked monthly, this allowed for 414 observations and 413 months of calculated returns to be derived. Table 3 gives an indication of the descriptive statistics for the monthly portfolio returns over the period of study (JSE12 model). Monthly return was derived from the monthly change in cumulative portfolio values. Logarithmic values were used to ensure that compounding was accounted for correctly. The standard deviation of each portfolio's monthly return data are also presented along with their variance, skewness and kurtosis values.

Table 3: Descriptive statistics: JSE12 model monthly return

	N	Mean Monthly Return	Std. Deviation Monthly	Variance Statistic	Skewness Statistic	Skewness Std. Error	Kurtosis Statistic	Kurtosis Std. Error
P1	413	1.39%	5.78%	33.39	-2.26	.120	16.32	.240
P2	413	1.38%	4.73%	22.38	-1.11	.120	4.61	.240
P3	413	1.10%	4.76%	22.69	-.94	.120	3.47	.240
P4	413	1.26%	4.86%	23.58	-.79	.120	3.69	.240
P5	413	0.83%	5.39%	29.06	-.66	.120	2.73	.240
Valid N (listwise)	413							

5.3.1.2 Graphical time-series representation

The performances of the quintile alpha based portfolios are shown in Figure 2, where the cumulative values of each portfolio are plotted against time. CAGRs provide a quantitative measure of each portfolio's performance. The cumulative value of the JSE ALSI is also indicated (represented by the J203TRI). The general trend in portfolio performance appeared to follow shares' alpha ranking, with P1 displaying the best performance and P5 displaying the worst performance. Both P1 and P2 outperformed the J203TRI. CAGRs ranged from 18.1% for P1 to 10.4% for P5. The CAGR for the J203TRI was 16.3%.

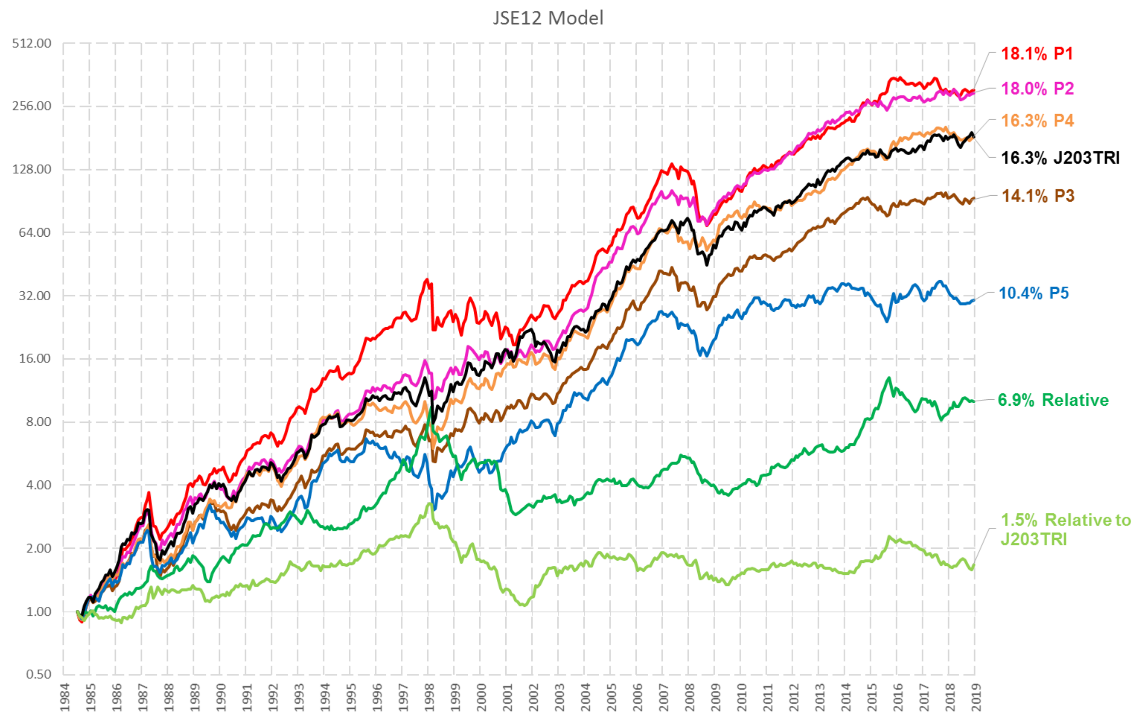

Figure 2: Graphical time-series representation of alpha based portfolios: JSE12 model

5.3.1.3 Relative performance

Two price relatives were constructed (Figure 2). The first price relative was calculated by dividing the cumulative value of P1 by the cumulative value of P5. The second price relative was calculated by dividing the cumulative value of P1 by the cumulative value of the J203TRI. This allowed for an intuitive visual comparison of performance of alpha as a style as well as performance relative to the market. The price relative between P1 and P5 was 6.9% at the end of the period of evaluation, while the price relative between P1 and the J203TRI was 1.5% at the end of the period of evaluation.

The slope of the price relative provided a graphical indication of the success associated with following alpha as an investment style. An upward slope was indicative of a period in which the style worked effectively and a divergence in return was observed between P1 and P5. A downward slope was indicative of the opposite, and could be interpreted as a period in which the style was not effective and a convergence in portfolio return observed. The same principal held true for the price relative constructed between P1 and the J203TRI.

5.3.1.4 Statistical tests for differences

Statistical tests were performed in addition to the graphical time-series approach presented in the previous section. Due to the importance of data distribution in determining the appropriate statistical test to be utilised (as highlighted in section 4.8.3.1), the Shapiro-Wilk test was initially used to determine if the data were normally or non-normally distributed at a significance level of 0.05. The Shapiro-Wilk test was favoured as it has been shown to be the most powerful test for normality for all types of distributions and sample sizes (Keskin, 2006; Razali & Yap, 2011). The Shapiro-Wilk test returned significant values (below the 0.05 level) for all portfolios (Table 4), rejecting the null hypothesis that the data were normally distributed. The alternate hypothesis that the data were non-normally distributed was therefore accepted.

Table 4: Shapiro-Wilk test for normality of distribution: JSE12 model

	Shapiro-Wilk		
	Statistic	df	Sig.
P1	.876	413	.000
P2	.950	413	.000
P3	.955	413	.000
P4	.958	413	.000
P5	.968	413	.000

As a result of the non-normal distribution of the data, non-parametric tests for differences had to be considered. The Jonckheere-Terpstra test for ordered alternatives was deemed most suitable based on the predicted order of the alternate hypothesis. The assumptions of independent observations of an ordinal or continuous level dependant variable, measured across more than two categories were satisfied for the performance of the Jockheere-Terpstra test. The Jonckheere-Terpstra test results indicated higher monthly returns were associated with lower portfolio numbers (higher alpha values) and that this trend was significant (Table 5). The null hypothesis was rejected in favour of the alternate hypothesis, which stated that portfolios constructed from higher alpha value shares performed better than portfolios constructed from lower alpha value shares over the period of the study.

Table 5: Jonckheere-Terpstra test results: JSE12 model

Jonckheere-Terpstra Test[a]

	Monthly return
Number of Levels in Portfolio	5
N	2065
Observed J-T Statistic	814867.000
Mean J-T Statistic	852845.000
Std. Deviation of J-T Statistic	15328.366
Std. J-T Statistic	-2.478
Asymp. Sig. (1-tailed)	.007

a. Grouping Variable: Portfolio

While the Jonckheere-Terpstra test results indicated that higher monthly returns were associated with lower portfolio numbers, and that this trend was significant, it did not indicate the location of the differences. In order to further investigate the differences in monthly return, *post hoc* pairwise analyses were performed. The *post hoc* results are presented in Table 6.

Table 6: *Post hoc* pairwise comparisons: JSE12 model

		Test Statistic	Std. Error	Std. Test Statistic	Sig. (1-tailed)	Adj. Sig. (1-tailed)
P1	P2	83,659.00	3,428.56	-.474	. 318	1.000
	P3	80,530.00	3,428.56	-1.387	.083	.828
	P4	81,021.00	3,428.56	-1.244	.107	1.000
	P5	77,661.00	3,428.56	-2.224	.013	.131
P2	P3	81,968.00	3,428.56	-.967	.167	1.000
	P4	82,574.00	3,428.56	-.791	.215	1.000
	P5	78,898.00	3,428.56	-1.863	.031	.312
P3	P4	85,527.00	3,428.56	.071	.472	1.000
	P5	81,789.00	3,428.56	-1.020	.154	1.000
P4	P5	81,240.00	3,428.56	-1.180	.119	1.000

*. The significance level is .05.

Post hoc pairwise comparisons of portfolios showed significant differences between P1 and P5 as well as between P2 and P5. However, a Bonferroni correction factor was applied to the significance levels in order to account for multiple comparisons. The inclusion of the Bonferroni correction factor was necessary to reduce the risk of type one errors when running multiple pair wise tests on a single data set (Bland & Altman, 1995). After applying the Bonferroni correction factor no significant differences between the performances of individual portfolios were observed.

5.3.2 Hypothesis 2

Hypothesis 2 was concerned with the difference in performance between a portfolio constructed from the highest alpha value shares and the market. P1 represented the portfolio constructed from shares displaying the highest alpha values and the JSE ALSI was used as the market. The performance of the JSE ALSI was represented by the J203TRI.

The null hypothesis stated that P1 underperformed or performed equally to the market. The alternate hypothesis stated that P1 outperformed the market.

$H2_0$: P1 ≤ JSE ALSI

$H2_a$: P1 > JSE ALSI

5.3.2.1 Descriptive statistics

Table 7 provides a summary of the descriptive statistics in the comparison of the monthly returns of P1 with the J203TRI.

Table 7: Descriptive statistics – P1 and J203TRI: JSE12 model

	N	Mean Monthly Return	Std. Deviation Monthly	Variance Statistic	Skewness Statistic	Skewness Std. Error	Kurtosis Statistic	Kurtosis Std. Error
P1	413	1.39%	5.78%	33.39	-2.26	.120	16.32	.240
J203TRI	413	1.26%	5.44%	29.60	-1.13	.120	5.74	.240
Valid N (listwise)	413							

5.3.2.2 Graphical time-series representation

The performances of P1 and the J203TRI are plotted in Figure 3. The price relative between P1 and the J203TRI is also shown. While P1 outperformed the market over the period of evaluation, much of the outperformance was observed in the initial 13 years of the study, and a relatively flat price relative was observed from 2005 onwards. Between 1998 and 2002 there was a four year period of substantial underperformance by P1 in relation to the J203TRI (Figure 3).

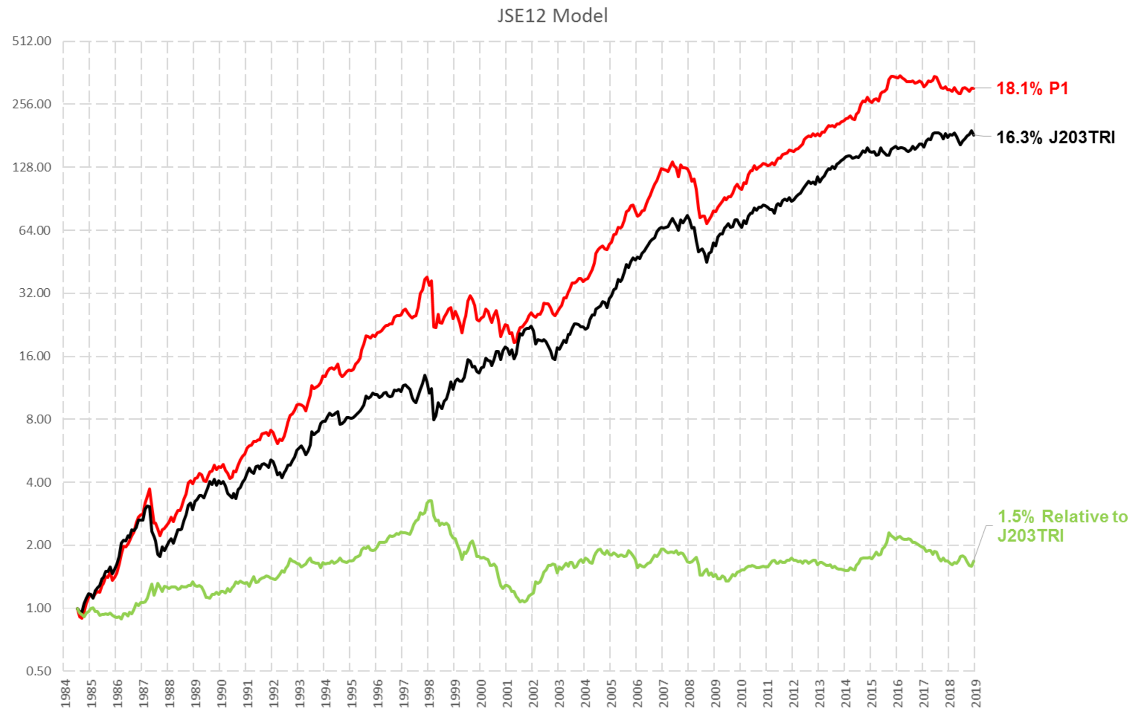

Figure 3: Graphical time-series representation of P1 and J203TRI: JSE12 model

5.3.2.3 Bootstrap analysis

'Style engine' data were used to create 100 random portfolios from the population of the JSE ALSI shares over the period of the study. The performance of these 100 portfolios is shown in Appendix A, Figure 13. The performance of the random portfolios at the upper and lower bounds of the 0.05 significance level are shown in Figure 4 and plotted against the performance of the alpha based portfolios over the period of the study.

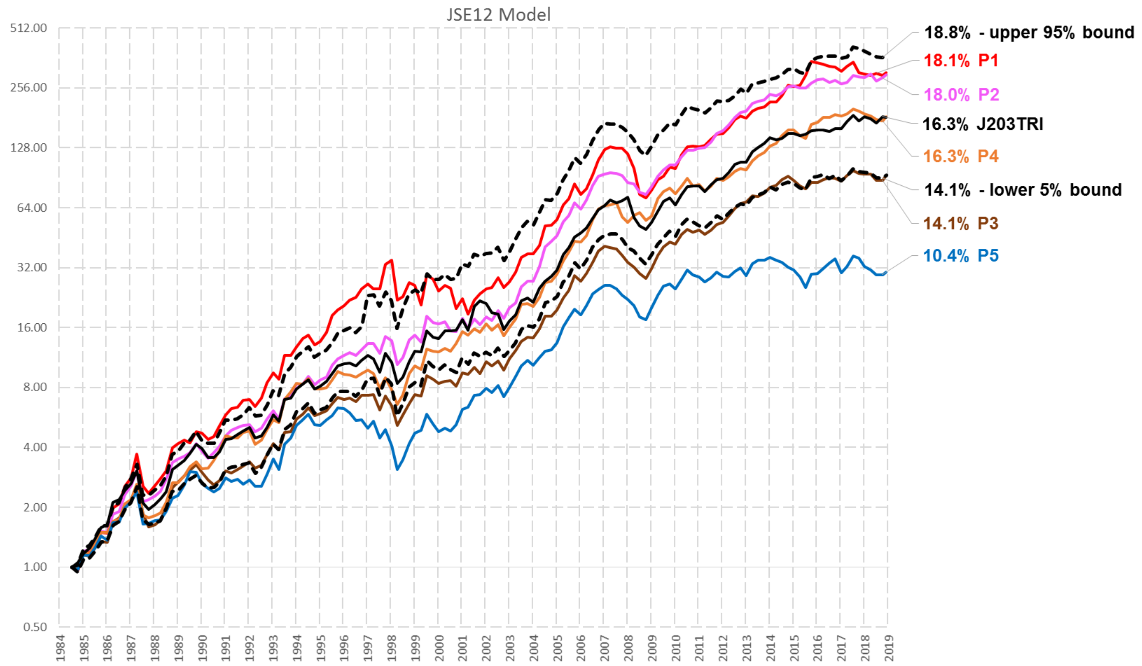

Figure 4: Upper and lower significance bounds of 100 random portfolios: JSE12 model

P1 failed to outperform the set of randomly generated portfolios at the 0.05 level. The distribution of the CAGRs of the 100 random bootstrap portfolios created from the 'style engine' data is shown in more detail in Figure 5. It is clear that 13 (13%) of the 100 random portfolios had CAGRs that exceeded the 18.1% CAGR achieved by P1. The results from the bootstrap analysis therefore indicate that the null hypothesis cannot be rejected at the 0.05 level.

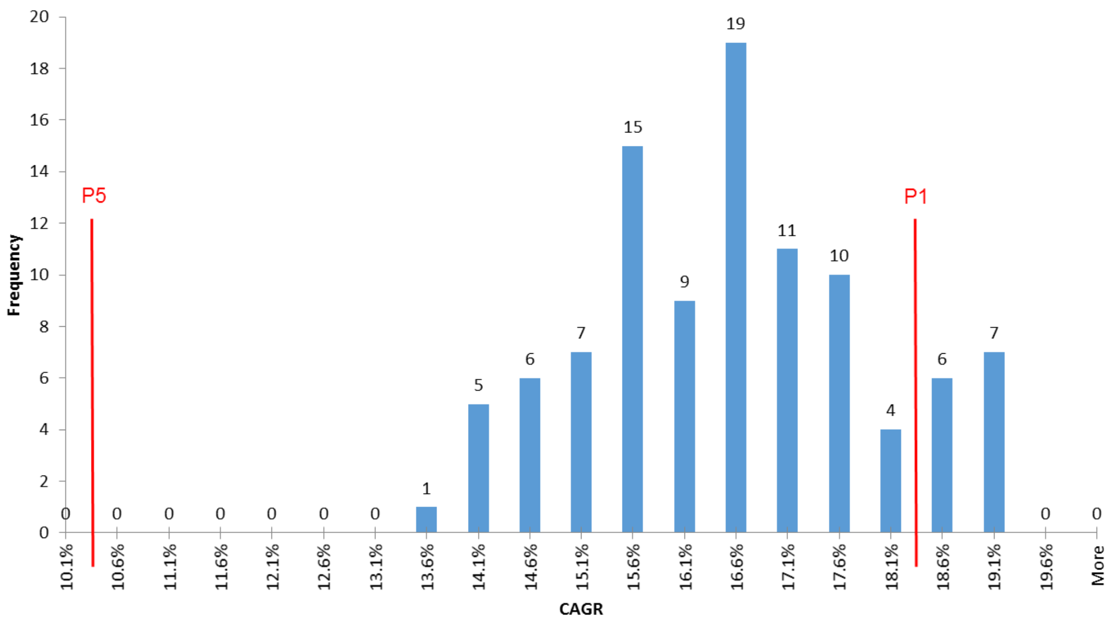

Figure 5: Distribution of 100 random portfolios: JSE12 model

5.3.2.4 Statistical tests for differences

The Shapiro-Wilk test returned significant values (below the 0.05 level) for P1 and the J203TRI, rejecting the null hypothesis that the monthly return data were normally distributed. The alternate hypothesis that the data was non-normally distributed was therefore accepted.

Table 8: Shapiro-Wilk test for normality of distribution of P1 and J203TRI: JSE12 model

	Shapiro-Wilk		
	Statistic	df	Sig.
P1	.876	413	.000
J203TRI	.943	413	.000

The non-parametric Wilcoxon signed-rank test was used to evaluate the significance of the difference in monthly return between P1 and the J203TRI.

Table 9: Wilcoxon signed-rank test ranks – J203TRI and P1: JSE12 model

		N	Mean Rank	Sum of Ranks
J203TRI - P1	Negative Ranks	213[a]	215.05	45805.00
	Positive Ranks	200[b]	198.43	39686.00
	Ties	0[c]		
	Total	413		

a. J203TRI < Portfolio 1

b. J203TRI > Portfolio 1

c. J203TRI = Portfolio 1

Table 10: Wilcoxon signed-rank test statistics[a] – J203TRI and P1: JSE12 model

	J203TRI - P1
Z	-1.260[b]
Asymp. Sig. (1-tailed)	.104

a. Wilcoxon Signed Ranks Test

b. Based on positive ranks.

The results showed that although P1's monthly returns outperformed that of the J203TRI in 213 out of 413 months, a significant difference in monthly returns was not observed at the 0.05 level. The results failed to reject the null hypothesis which stated that P1 underperformed or performed equally to the market.

5.3.3 Hypothesis 3

Hypothesis 3 was concerned with the difference in performance between a portfolio constructed from the lowest alpha value shares and the market. P5 represented the portfolio constructed from shares displaying the lowest alpha values and the JSE ALSI was used as the market. The performance of the JSE ALSI was represented by the J203TRI.

The null hypothesis stated that P5 outperformed or performed equally to the market. The alternate hypothesis stated that P5 underperformed the market.

$H3_0$: P5 ≥ JSE ALSI

$H3_a$: P5 < JSE ALSI

5.3.3.1 Descriptive statistics

Table 11 provides a summary of the descriptive statistics in the comparison of P5 with the J203TRI.

Table 11: Descriptive statistics – P5 and J203TRI: JSE12 model

	N	Mean Monthly Return	Std. Deviation Monthly	Variance Statistic	Skewness Statistic	Std. Error	Kurtosis Statistic	Std. Error
P5	413	0.83%	5.39%	29.06	-.66	.120	2.73	.240
J203TRI	413	1.26%	5.44%	29.60	-1.13	.120	5.74	.240
Valid N (listwise)	413							

5.3.3.2 Graphical time-series representation

The performances of P5 and the J203TRI are shown in Figure 6. The price relative between P5 and the J203TRI is also shown. The J203TRI consistently outperformed P5 over the entire period of the investigation as evidenced by the consistently downward slope in price relative.

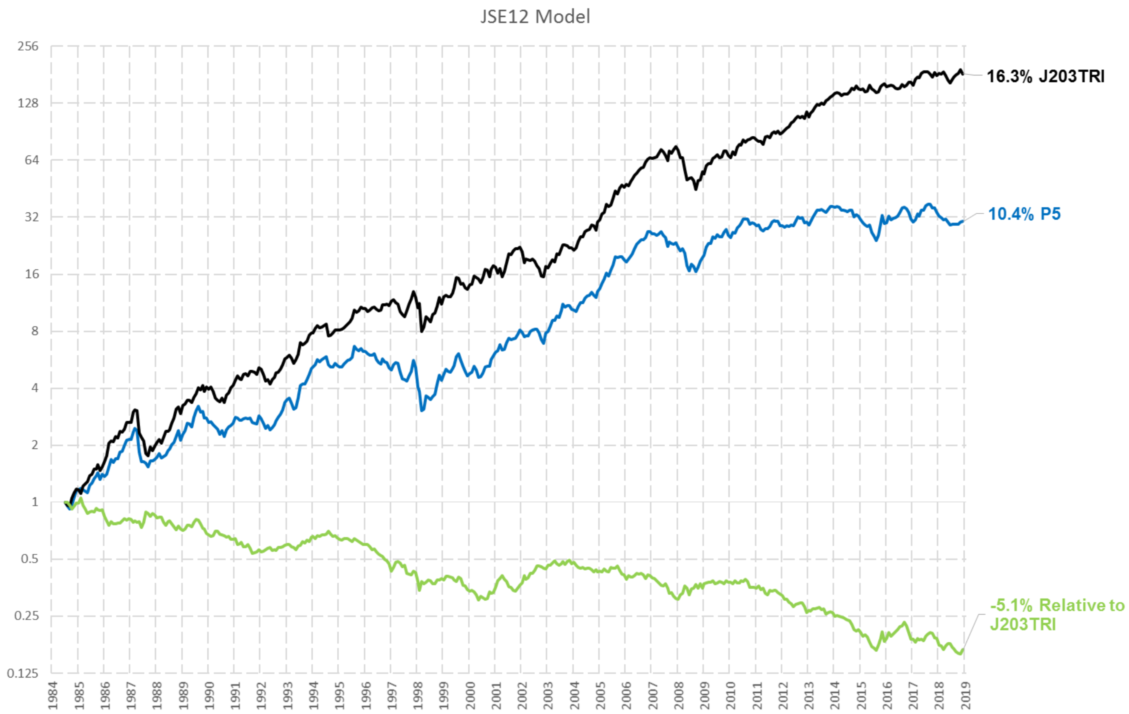

Figure 6: Graphical time-series representation of P5 and J203TRI: JSE12 model

5.3.3.3 Bootstrap analysis

Referring to Figure 4 and Figure 5 it was observed that each of the 100 random JSE ALSI portfolios performed in excess of the 10.4% CAGR achieved by P5. The worst performing random portfolio displayed a CAGR of 13.5%. The results from the bootstrap analysis therefore rejected the null hypothesis that P5 outperformed or performed equally to the market.

5.3.3.4 Statistical tests for differences

The statistical testing method followed the same process outlined in the evaluation of Hypothesis 2 in which the data were first evaluated for normality, and then a test for differences was performed. The results of these tests are given below.

Shapiro-Wilk tests (Table 4 and Table 8) indicated that the data for P5 and the J203TRI were non-normally distributed. The non-parametric Wilcoxon signed-rank test was used to evaluate the significance of the difference in monthly returns between P5 and the J203TRI.

Table 12: Wilcoxon signed-rank test ranks – P5 and J203TRI: JSE12 model

		N	Mean Rank	Sum of Ranks
P5 - J203TRI	Negative Ranks	230[a]	214.43	49318.00
	Positive Ranks	183[b]	197.67	36173.00
	Ties	0[c]		
	Total	413		

a. P5 < J203TRI

b. P5 > J203TRI

c. P5 = J203TRI

Table 13: Wilcoxon signed-rank test statistics[a] - P5 and J203TRI: JSE12 model

	P5 - J203TRI
Z	-2.708[b]
Asymp. Sig. (1-tailed)	.003

a. Wilcoxon Signed Ranks Test

b. Based on positive ranks.

The results showed that the monthly returns of P5 underperformed those of the J203TRI in 230 out of 413 months. Further, the difference was significant at the 0.05 level. The null hypothesis was therefore rejected in favour of the alternate hypothesis which stated that P5 underperformed the market.

5.4 Fama-French five factor model

The results presented in this section relate to alpha values calculated using the Fama-French five factor (FF5) model. The same hypotheses and data analyses approaches as those conducted in section 5.3 are presented below, but the alpha values of JSE listed shares were calculated using the FF5 model.

5.4.1 Hypothesis 1

Hypothesis 1 was concerned with the differences in returns among portfolios that were constructed using the alpha value of JSE listed shares as a basis for ranking the shares.

The null hypothesis stated that portfolios constructed from higher alpha value shares would perform equally to, or worse than, portfolios constructed from lower alpha value shares over the period of evaluation. The alternate hypothesis stated that portfolios constructed from higher alpha value shares would perform better than portfolios constructed from lower alpha value shares over the period of evaluation.

$H1_0$: P1 ≤ P2 ≤ P3 ≤ P4 ≤ P5
$H1_a$: P1 > P2 > P3 > P4 > P5

5.4.1.1 Descriptive statistics

Section 5.4.1.1 outlines the data set and the performance of the portfolios. Figure 7 indicates the mean quarterly alpha values of the constituents of each portfolio over the period of the study, using the FF5 model. P1 represents shares with the highest alpha values while P5 represents the shares with the lowest alpha values.

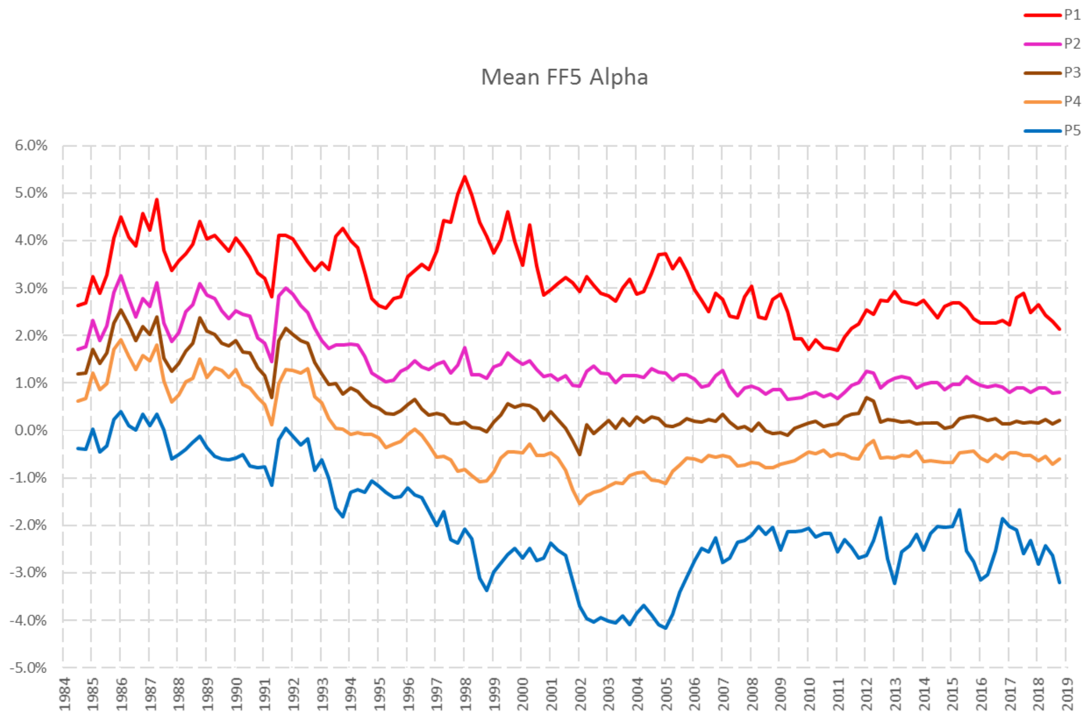

Figure 7: Mean quintile alpha values: FF5 model

Table 14 gives an indication of the descriptive statistics for the monthly portfolio returns over the period of study (FF5 model). The standard deviation of each portfolios' monthly return data are also presented along with their variance, skewness and kurtosis values.

Table 14: Descriptive statistics: FF5 model monthly return

	N	Mean Monthly Return	Std. Deviation Monthly	Variance Statistic	Skewness Statistic	Skewness Std. Error	Kurtosis Statistic	Kurtosis Std. Error
P1	413	1.17%	5.85%	34.19	-2.10	.120	14.47	.240
P2	413	1.36%	4.87%	23.76	-1.41	.120	8.25	.240
P3	413	1.21%	4.76%	22.65	-.94	.120	4.10	.240
P4	413	1.31%	4.67%	21.77	-.60	.120	1.95	.240
P5	413	0.85%	5.50%	30.26	-.32	.120	1.47	.240
Valid N (listwise)	413							

5.4.1.2 Graphical time-series representation

The performances of the quintile alpha based portfolios are shown in Figure 8, where the cumulative values of each portfolio are plotted against time. The cumulative value of the J203TRI is also indicated. CAGRs ranged from 17.9% for P2 to 10.7% for P5. The CAGR of the J203TRI was 16.3%. No general trend in portfolio performance was apparent. P2 was the top performing portfolio while P1 underperformed all portfolios except for P5. P5 was the worst performing portfolio with a CAGR of 10.7%. Two price relatives were added to the graphical time-series representation to aid visual interpretation. The first price relative was calculated by dividing the cumulative value of P1 by the cumulative value of P5. The second price relative was calculated by dividing the cumulative value of P1 by the cumulative value of the J203TRI. No consistent pattern was observed in either price relative with periods of upward and downward slope present as well as extended flat periods.

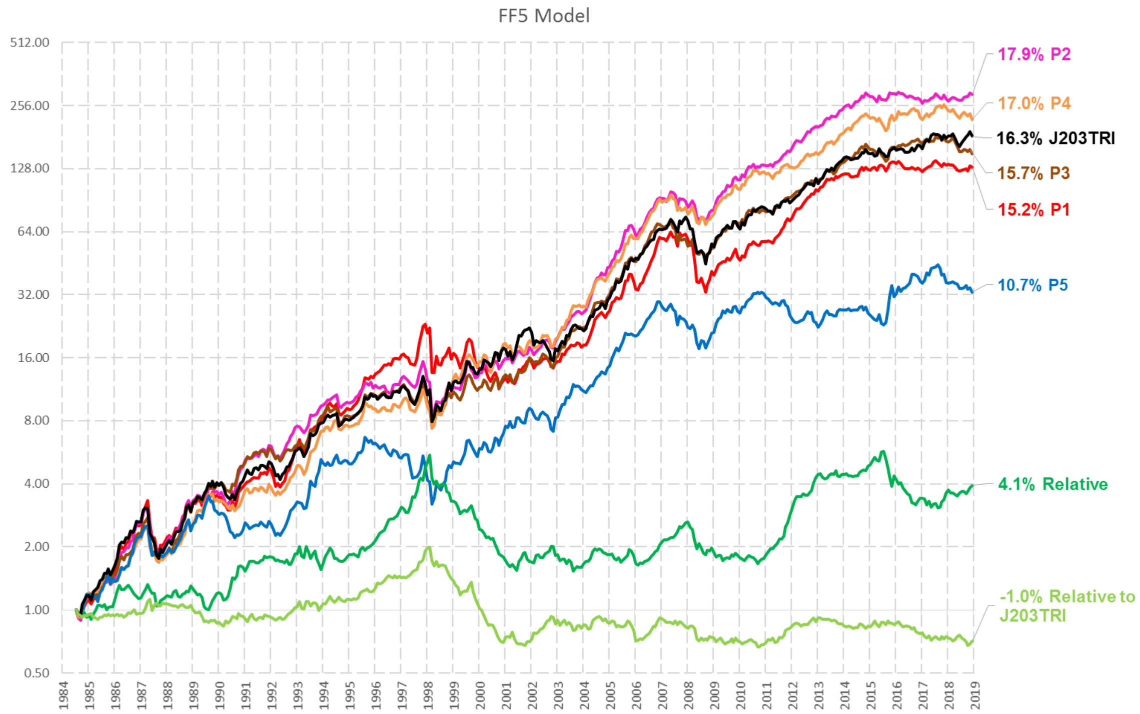

Figure 8: Graphical time-series representation of alpha based portfolios: FF5 model

5.4.1.3 Statistical tests for differences

Statistical tests were performed in addition to the graphical time-series approach presented in the previous section. The Shapiro-Wilk test for normality returned significant values (below the 0.05 level) for all portfolios, rejecting the null hypothesis that the data were normally distributed.

Table 15: Shapiro-Wilk test for normality of distribution: FF5 model

	Shapiro-Wilk		
	Statistic	df	Sig.
P1	.882	413	.000
P2	.925	413	.000
P3	.953	413	.000
P4	.977	413	.000
P5	.983	413	.000

The non-parametric Jonckheere-Terpstra test for ordered alternatives was conducted under the prediction of higher monthly returns associated with lower portfolio numbers. The Jonckheere-Terpstra test results indicated higher monthly returns were associated with lower portfolio numbers (higher alpha values) and that the trend was significant (Table 16). The null hypothesis was rejected, in favour of the alternate hypothesis, which stated that portfolios constructed from higher alpha value shares performed better than portfolios constructed from lower alpha value shares over the period of the study.

Table 16: Jonckheere-Terpstra test results: FF5 model

Jonckheere-Terpstra Test[a]

	Monthly return
Number of Levels in Portfolio	5
N	2065
Observed J-T Statistic	823217.000
Mean J-T Statistic	852845.000
Std. Deviation of J-T Statistic	15328.366
Std. J-T Statistic	-1.933
Asymp. Sig. (1-tailed)	.027

a. Grouping Variable: Portfolio

As with the JSE12 model, further investigation of the location of differences in monthly return of the various portfolios required a *post hoc* analysis. The *post hoc* results are presented in Table 17.

Table 17: *Post hoc* pairwise comparisons: FF5 model

		Test Statistic	Std. Error	Std. Test Statistic	Sig. (1-tailed)	Adj. Sig. (1-tailed)
P1	P2	85,717.00	3,428.56	.126	. 450	1.000
	P3	83,547.00	3,428.56	-0.507	.306	1.000
	P4	84,269.00	3,428.56	-.296	.384	1.000
	P5	79,048.00	3,428.56	-1.819	.034	.345
P2	P3	83,053.00	3,428.56	-.651	.258	1.000
	P4	83,736.00	3,428.56	-.452	.326	1.000
	P5	78,117.00	3,428.56	-2.091	.018	.183
P3	P4	85,906.00	3,428.56	.181	.428	1.000
	P5	80178.00	3,428.56	-1.489	.068	.682
P4	P5	79,646.00	3,428.56	-1.645	.050	.500

*. The significance level is .05.

Similarly to the JSE12 model results, *post hoc* pairwise comparisons of portfolios showed significant differences between P1 and P5 as well as between P2 and P5. However, once the Bonferroni correction factor was applied in order to account for multiple comparisons, no significant differences between individual portfolios were observed.

5.4.2 Hypothesis 2

Hypothesis 2 was concerned with the difference in performance between a portfolio constructed from the highest alpha value shares and the market. P1 represented the portfolio constructed from shares displaying the highest alpha values and the JSE ALSI was used as the market. The performance of the JSE ALSI was represented by the J203TRI.

The null hypothesis stated that P1 underperformed or performed equally to the market. The alternate hypothesis stated that P1 outperformed the market.

$H2_0$: P1 ≤ JSE ALSI

$H2_a$: P1 > JSE ALSI

5.4.2.1 Descriptive statistics

Table 18 provides a summary of the descriptive statistics in the comparison of the monthly returns of P1 with the J203TRI.

Table 18: Descriptive statistics – P1 and J203TRI: FF5 model

	N	Mean Monthly Return	Std. Deviation Monthly	Variance Statistic	Skewness Statistic	Skewness Std. Error	Kurtosis Statistic	Kurtosis Std. Error
P1	413	1.17%	5.85%	34.17	-2.10	.120	14.47	.240
J203TRI	413	1.26%	5.44%	29.60	-1.13	.120	5.74	.240
Valid N (listwise)	413							

5.4.2.2 Graphical time-series representation

The performance of P1 and the J203TRI are plotted in Figure 9. The price relative between P1 and the J203TRI is also shown. As with the JSE12 model, 1998 to 2002 marked a period of substantial underperformance by P1 in relation the J203TRI, followed by a long period of flat relative performance.

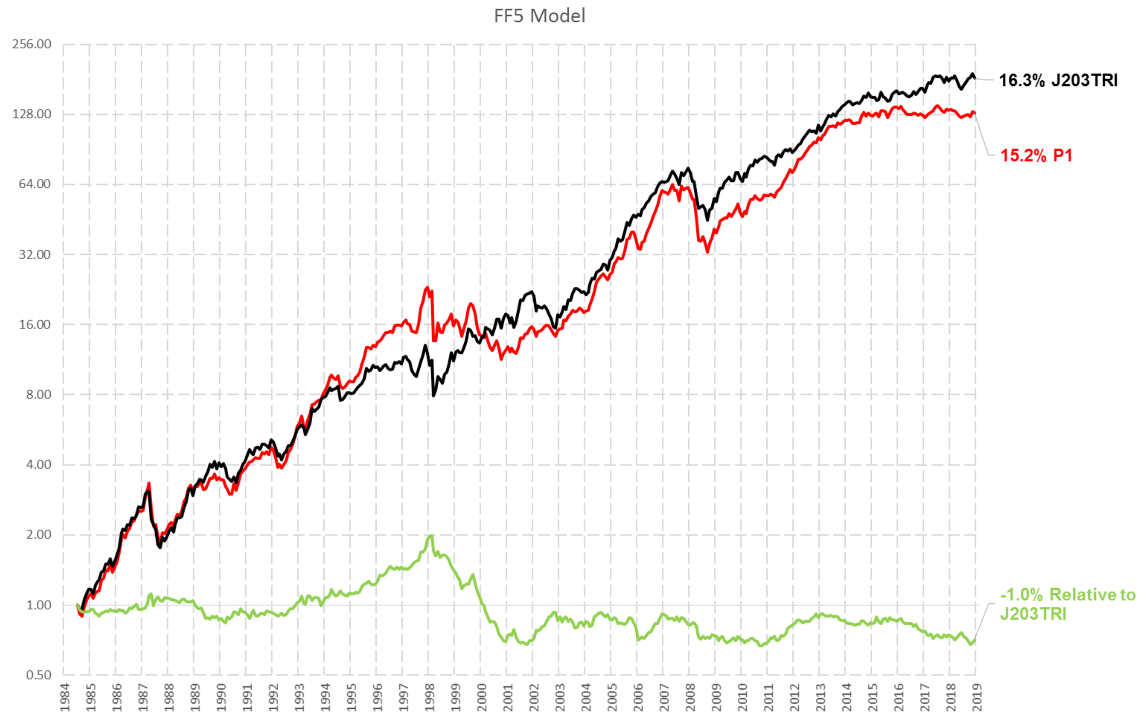

Figure 9: Graphical time-series representation of P1 and J203TRI: FF5 model

5.4.2.3 Bootstrap analysis

‘Style engine’ data were used to create 100 random portfolios from the population of the JSE ALSI shares over the period of the study. The performance of these 100 portfolios is shown in Appendix A, Figure 14. The performance of the random portfolios at the upper and lower bounds of the 0.05 significance level are shown in Figure 10 and plotted against the performance of the alpha based portfolios over the period of the study.

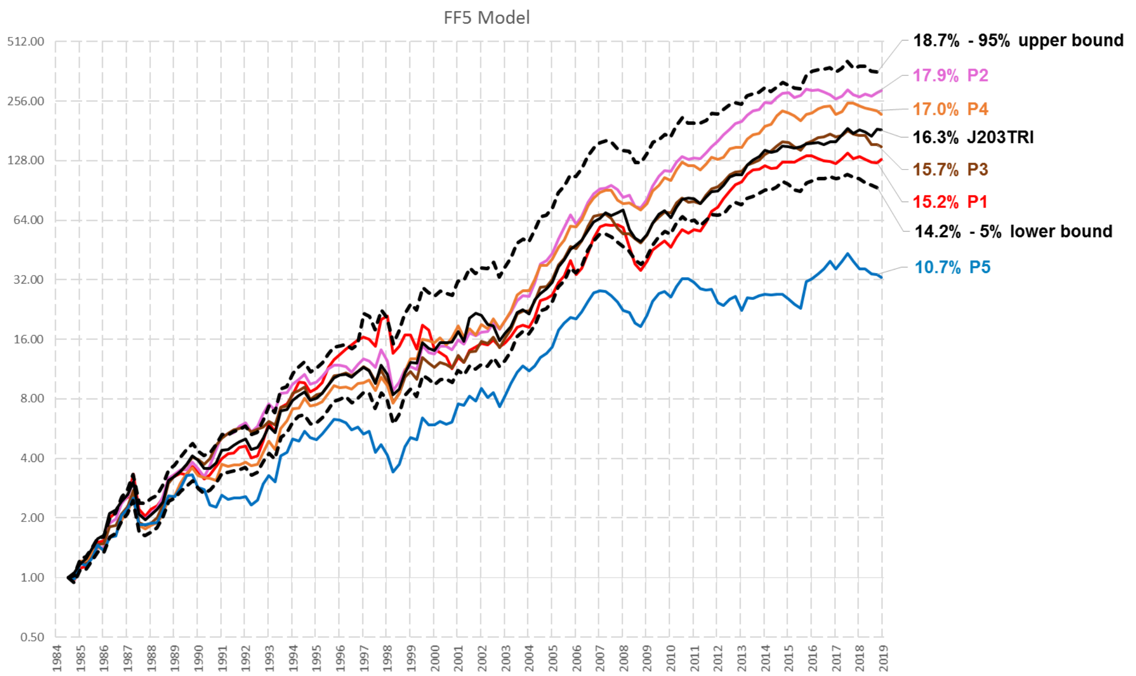

Figure 10: Upper and lower significance bounds of 100 random portfolios: FF5 model

P1 failed to outperform the set of randomly generated portfolios at the 0.05 level, and thus the null hypothesis could not be rejected. A more detailed examination of the distribution of the CAGR of the 100 random bootstrap portfolios indicates that 73 (73%) of the 100 random portfolios performed in excess of the 15.2% CAGR achieved by P1 (Figure 11).

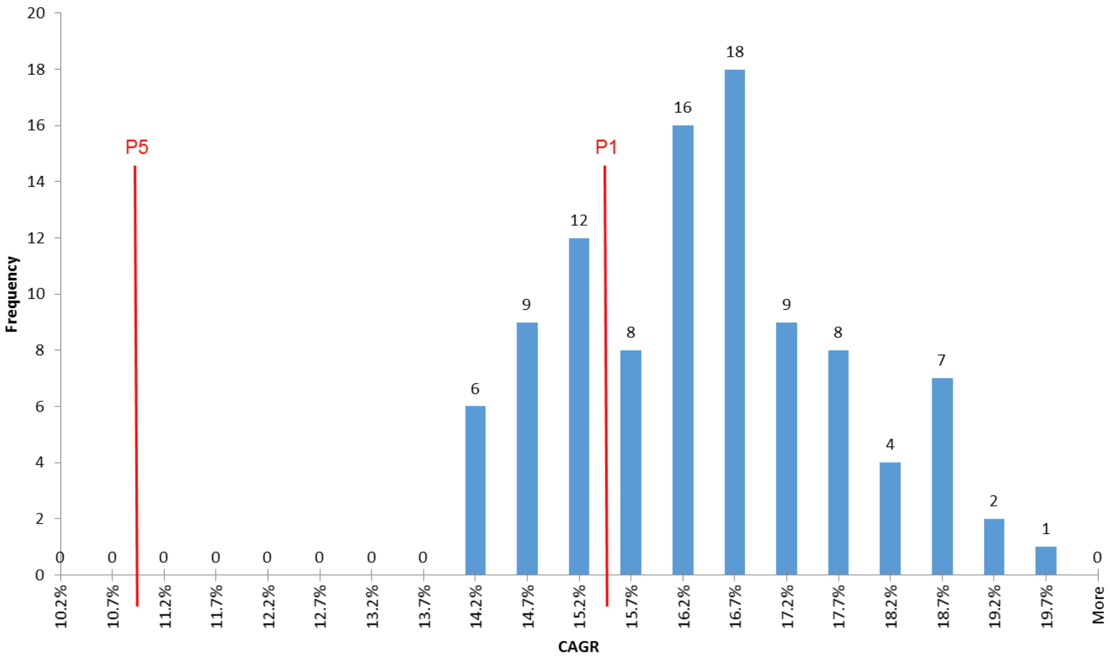

Figure 11: Distribution of 100 random portfolios: FF5 model

5.4.2.4 Statistical tests for differences

Shapiro-Wilk tests (Table 8 and Table 15) indicated that data for P1 and the J203TRI were non-normally distributed. The non-parametric Wilcoxon signed-rank test was used to evaluate the significance of the difference in monthly returns between P1 and the J203TRI.

Table 19: Wilcoxon signed-rank test ranks – J203TRI and P1: FF5 model

		N	Mean Rank	Sum of Ranks
J203TRI - P1	Negative Ranks	207[a]	207.18	42886.00
	Positive Ranks	206[b]	206.82	42605.00
	Ties	0[c]		
	Total	413		

a. JSE < P1

b. JSE > P1

c. JSE = P1

Table 20: Wilcoxon signed-rank test statistics[a] – J203TRI and P1: FF5 model

	J203TRI - P1
Z	-.058[b]
Asymp. Sig. (1-tailed)	.477

a. Wilcoxon Signed Ranks Test

b. Based on positive ranks.

The results showed that while P1's monthly returns outperformed those of the J203TRI in 207 out of 413 months, a significant difference in monthly return was not observed at the 0.05 level. This resulted in failure to reject the null hypothesis which stated that P1 underperformed or performed equally to the market.

5.4.3 Hypothesis 3

Hypothesis 3 was concerned with the difference in performance between a portfolio constructed from shares displaying the lowest alpha values and the market. P5 represented the portfolio constructed from shares displaying the lowest alpha values and the JSE ALSI represented the market. The performance of the JSE ALSI was represented by the J203TRI.

The null hypothesis stated that P5 outperformed or performed equally to the market. The alternate hypothesis stated that P5 underperformed the market.

$H3_0$: P5 ≥ JSE ALSI

$H3_a$: P5 < JSE ALSI

5.4.3.1 Descriptive statistics

Table 21 provides a summary of the descriptive statistics in the comparison of P5 with the J203TRI.

Table 21: Descriptive statistics – P5 and J203TRI: FF5 model

	N	Mean Monthly Return	Std. Deviation Monthly	Variance Statistic	Skewness Statistic	Skewness Std. Error	Kurtosis Statistic	Kurtosis Std. Error
P5	413	0.85%	5.50%	30.26	-.32	.120	1.47	.240
J203TRI	413	1.26%	5.44%	29.60	-1.13	.120	5.74	.240
Valid N (listwise)	413							

5.4.3.2 Graphical time-series representation

The performance of P5 and the J203TRI is shown in Figure 12. The price relative between P5 and the J203TRI is also shown. The J203TRI consistently outperformed P5 over the entire period of the investigation as evidenced by the consistently downward slope in price relative.

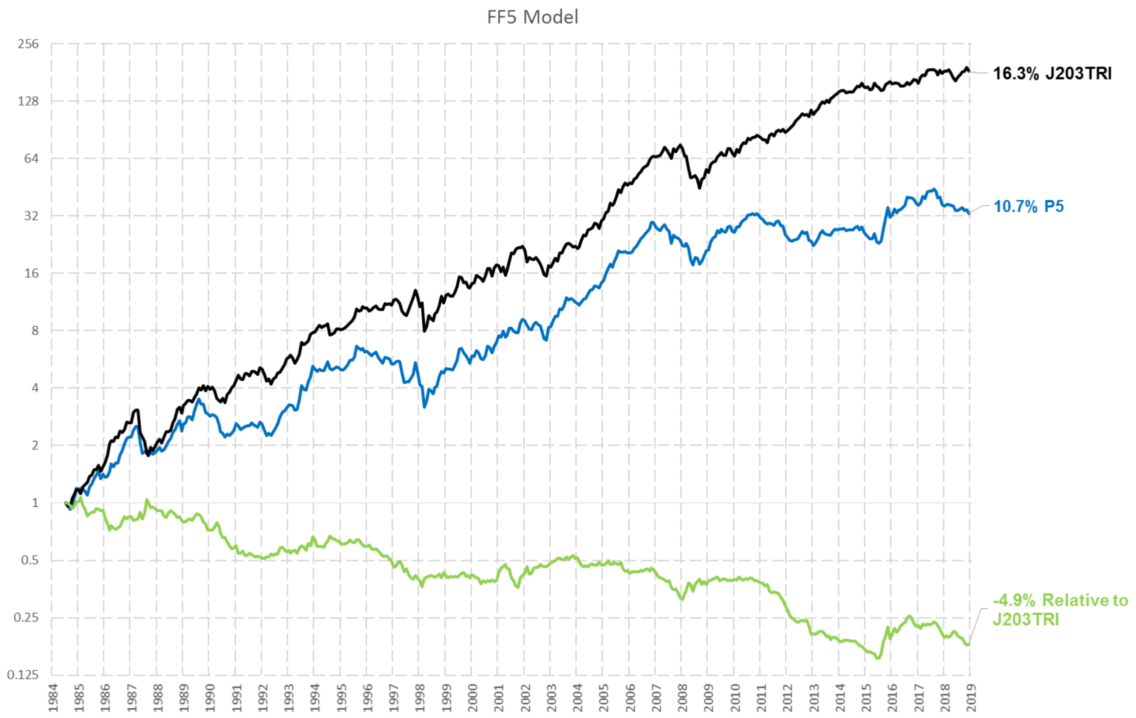

Figure 12: Graphical time-series representation of P5 and J203TRI: FF5 model

5.4.3.3 Bootstrap analysis

Referring to Figure 10 and Figure 11 it was observed that all 100 random JSE ALSI portfolios performed in excess of the 10.7% CAGR achieved by P5. The worst performing random portfolio displayed a CAGR of 13.7%. The results from the bootstrap analysis therefore rejected the null hypothesis which stated that P5 outperformed or performed equally to the market.

5.4.3.4 Statistical tests for differences

Shapiro-Wilk tests (Table 8 and Table 15) indicated that data for P5 and the J203TRI were non-normally distributed. The non-parametric Wilcoxon signed-rank test was used to evaluate the significance of the difference in monthly returns between P5 and the J203TRI.

Table 22: Wilcoxon signed-rank test ranks – P5 and J203TRI: FF5 model

		N	Mean Rank	Sum of Ranks
P5 – J203TRI	Negative Ranks	233[a]	211.79	49348.00
	Positive Ranks	180[b]	200.79	36143.00
	Ties	0[c]		
	Total	413		

a. P5 < J203TRI

b. P5 > J203TRI

c. P5 = J203TRI

Table 23: Wilcoxon signed-rank test statistics[a] - P5 and J203TRI: JSE12 model

	P5 – J203TRI
Z	-2.720[b]
Asymp. Sig. (1-tailed)	.003

a. Wilcoxon Signed Ranks Test

b. Based on positive ranks.

The results showed that the monthly returns of P5 underperformed those of the J203TRI in 233 out of 413 months. Further, the difference was significant at the 0.05 level. The null hypothesis was therefore rejected in favour of the alternate hypothesis which stated that P5 underperformed the market.

Chapter 6: Discussion of results

6.1 Introduction

The obtained results are discussed in the following section. The results are analysed in terms of the hypotheses set out in Chapter 3 and their relation to the literature reviewed in Chapter 2. The general results suggested an association between alpha and return, with portfolios constructed from high alpha shares outperforming low alpha portfolios and significant underperformance in relation to the market observed in portfolios constructed from the lowest alpha shares. However, differences in performance between high alpha portfolios and the market were not statistically significant.

6.2 Hypothesis 1

Hypothesis 1 evaluated historical JSE data generated between 1985 and 2019 to determine the existance of alpha as an investment style. The null hypothesis stated that portfolios of shares constructed from higher alpha value shares would perform equally to, or worse than, portfolios of shares constructed from lower alpha value shares.

6.2.1 JSE twelve factor model

Examining the graphical time-series analysis (Figure 2), the ranking of the portfolios generally followed the expected trend with P1 displaying the best performance and P5 displaying the worst performance. The mean monthly return of the various portfolios (Table 3) indicated the same trends. The slope of the price relative between P1 and P5 is predominantly upward indicating that the style worked most of the time. Three periods of consistent downward slope must however be highlighted: between 1998 and 2001, 2008 and 2009 as well as between 2016 and 2018. In two of the three periods the change in slope direction corresponds to a drawdown in the JSE ALSI. The first of these was caused by the Asian stock market crash of 1998 that spilt over into many emerging markets while the latter period related to the 2008 global financial crisis. The overall slope does however indicate persistent outperformance by high alpha value portfolios in comparison to low alpha value portfolios, with market crashes a potential indicator of periods of trend reversal.

Non-parametric statistical testing (the Jonckheere-Terpstra test), confirmed a statistically significant trend between higher alpha value portfolios and increased performance. A p*ost hoc* analysis revealed that the biggest difference existed between the outer portfolios (P1 and P5, Table 6). However, the analyses conducted involved multiple comparisons in which several statistical tests were performed simultaneously so the significance levels of the individual comparisons had to be adjusted to preclude Type 1 errors (falsely asserting significant differences). After the application of a Bonferroni correction factor, differences in monthly returns between individual portfolios were deemed insignificant. It must be noted that one of the concerns associated with the Bonferroni correction is the loss of power associated with a larger number of comparisons and the resultant increase in Type 2 error rates (Streiner & Norman, 2011). Nevertheless, the insignificant *post hoc* results related to the differences between individual portfolios did not detract from the overall significance in the associated trend between higher alpha value portfolios and increased performance.

In the context of broader financial theory, the existence of a predictable pattern in stock prices supports the proposition that investors are capable of exploiting patterns in stock markets as well as the existence of persistent styles on the JSE. The results support the proposal that alpha is a feasible investment style on the JSE when alpha is derived from the JSE12 model. The results are also consistent with international findings in developed markets, where higher alpha levels have been associated with increased performance (Chong et al., 2017; Hühn & Scholz, 2018) albeit under different models for expected return.

6.2.2 Fama-French five factor model

Figure 8 shows the graphical time-series analysis of the individual portfolios' performance under the FF5 model. As expected P5 shows persistent underperformance in relation to all other portfolios. Against expectation, P2 displays the best performance over the duration of the study followed by P4, P3 and P1. There is some evidence of portfolios performing in line with expectation up until 1998, after which P1 experienced a four year period of severe underperformance from which it never recovered. However, over this period P2, P3 and P4 continued to perform well, ultimately delivering better returns than P1. The slope of the price relative between P1 and P5 is predominantly upward between 1985 and 1998, providing evidence of the style working over this period. This is followed by a downward slope between 1998 and 2001 indicating that P5 outperformed P1 over this period. The years between 2001 and 2011 show a period of flat relative performance, with an upward slope again observed between 2011 and 2015 and a downward slope between 2015 and 2018. While an additional 4.1% in CAGR was observed in P1 over P5 over the full duration of the study, the overall slope is less obviously consistently upward when compared to the JSE12 model (Figure 2).

Non-parametric statistical testing (the Jonckheere-Terpstra test), did confirm a statistically significant trend between higher alpha value portfolios and increased performance (Table 16). As with the JSE12 model, a *post hoc* analysis revealed that the biggest difference was found between the outer portfolios (P2 and P5), while individual differences were deemed insignificant after the application of a Bonferroni correction factor. The statistically significant trend found between higher alpha value portfolios and increased performance is attributed to the scale of underperformance displayed by P5 in relation to all other portfolios, as well as the initial 1985 to 1998 period during which portfolio performance ranking was somewhat in line with expectation.

The results cast some doubt on alpha as a feasible investment style on the JSE, when alpha is derived from the FF5 model for expected return. While P1 did outperform P5 over the duration of the study, periods of strong reversal in trend and extended flat periods were observed in the price relative, and investors would need to rely on market timing to some degree in order to make it a successful investment style. This result is contradictory to international findings on alpha, where a clear and distinct order has been observed in performance when ranking stocks according to alpha values (Chong et al., 2017; Hühn & Scholz, 2018). A possible explanation for this relates to the fit of the model for expected return. Owing to the index nature of the study population (JSE ALSI) it was expected that the average alpha value across the population would be zero (Jensen, 1968), or close to it. While the JSE12 model appears to be a relatively good fit on the JSE (displaying an average alpha value of -0.11% over the period of study), the FF5 model appears not to fit the JSE as well (displaying an average alpha value of 0.63% over the period of study; Table 2). Questions about the fit of the FF5 model on the JSE are also raised by Figure 7 which plots the mean quarterly alpha values of the different portfolios under the FF5 model. Early years (1985 to 1999) show a positive bias in quintiles, with alpha values not evenly distributed around zero as would be expected. This result is not surprising given that global pricing models, like the FF5 model, do not perform well when explaining regional returns (Fama & French, 2012). There is also clear evidence of the need to separate developed and emerging markets when pricing assets (Cakici et al., 2013). The high mean alpha values (Table 2) indicate that alpha is probably partly a surrogate for a combination of other factors and reflects some degree of mispricing in the FF5 model on the JSE. This explanation is supported by Stambaugh and Yuan (2016) who put forward the notion that a multitude of pricing anomalies may be captured by a single mispricing proxy alpha term, to better explain the cross-section of expected returns.

6.2.3 Conclusion: Hypothesis 1

Using alpha as an investment style on the JSE is highly dependent on the model for expected return from which alpha is derived from. The JSE12 model appears to be a superior model to the FF5 model when evaluating shares on the JSE, displaying average alpha values much closer to zero over the period of study. This indicates an evaluation of alpha alone under the JSE12 model, while the higher average alpha values resulting from the FF5 model indicate a possible grouping of other factors into the evaluated alpha variable. Under the JSE12 model a significant spread is observed between P1 and P5 and the portfolios largely follow the expected order over the duration of the time-series. Statistical tests confirm a significant trend of increased performance in higher alpha value portfolios. Under the FF5 model a spread between P1 and P5 is also observed, however, with the exception of P5, the portfolios do not follow the expected order over the duration of the time-series. This is in contrast to international findings from similar portfolio based studies on alpha, but is likely due to the fit of the FF5 model on the JSE. While statistical tests confirm a significant trend of increased performance in higher alpha value portfolios under the FF5 model, this is likely to be a result of the very poor returns associated with the portfolio with the lowest alpha value shares (P5), rather than the predictability of the order of returns associated with the portfolios with higher alpha values. It may also be partly a result of the initial 14 years of the study where portfolios behaved somewhat in line with expectation.

6.3 Hypothesis 2

Hypothesis 2 was concerned with the difference in performance between a portfolio constructed from the highest alpha value shares and the market. P1 represented a portfolio constructed from the highest alpha value shares while the JSE ALSI represented the market. The null hypothesis stated that P1 underperformed or performed equally to the market.

6.3.1 JSE twelve factor model

P1 consisted of a portfolio of shares that displayed a mean alpha value of 2.42% (Table 2). The price relative indicates that the majority of outperformance of P1 in relation to the market was in the early years of evaluation, with a persistent upward slope between 1986 and 1998. This was followed by a persistent downward slope between 1998 and 2002. From 2003 onwards little evidence of any association was present with a largely flat price relative indicating that the P1 and the market delivered similar returns. The behaviour of the price relative indicates that the performance associated with high alpha value shares is not consistently in excess of that of the market, displaying alternating periods of outperformance, underperformance and equal performance.

Figure 4 shows the performance of P1 in relation to upper and lower significance bounds of 100 random bootstrap portfolios. P1 failed to outperform a set of random portfolios at a significance level of 0.05, indicating that the outperformance observed in the graphical time-series representation was not significant. The distribution of the CAGR's of the 100 randomly generated portfolios (Figure 5) clearly shows that 13% of randomly generated portfolios outperformed P1. The results of the bootstrap analysis correspond with the lack of a consistent relative trend observed in the graphical time-series analysis.

Statistical analyses, in the form of the Wilcoxon signed-rank test, of the monthly returns of P1 and the JSE ALSI also failed to reject the null hypothesis which stated that a portfolio constructed from the highest alpha value shares underperformed or performed equally to the market. This supported the observations of the graphical time-series analysis and the results of the bootstrap analysis.

The results shed additional light on the behavioural characteristics of alpha as an investment style by evaluating a long only portfolio in relation to the market, as opposed to the traditional market neutral portfolio style employed by Chong et al. (2017). Market neutral portfolios combine long and short positions in winner and loser portfolios and this approach makes it difficult to identify whether the winner or loser portfolio drives the majority of performance. The failure of P1 to significantly outperform the market is not surprising given the stock-specific nature of alpha and the observations of Grundy and Martin (2001) during their investigation of a stock-specific momentum strategy. Grundy and Martin (2001) noted that the strategy's profits were driven by its short positions, while the long positions did not generate statistically significant risk-adjusted profits.

6.3.2 Fama-French five factor model

P1 consisted of a portfolio of shares that displayed a mean alpha value of 3.18% (Table 2) and underperformed the market, displaying a CAGR of -1.0% in relation to the market over the period of evaluation (Figure 9). The price relative shows that P1 outperformed the market between 1990 and 1998, however this trend reverses sharply in 1998 and a steep downward slope was observed up until 2001. From 2001 onwards, little evidence of any association was present with a largely flat price relative. As with the JSE12 model there is little evidence of consistency in the price relative, and periods of outperformance are mixed with periods of underperformance, while the last 18 years displayed little difference in performance.

Figure 10 shows the performance of P1 in relation to upper and lower significance bounds of 100 random bootstrap portfolios. P1 failed to outperform a set of random portfolios at a significance level of 0.05, resulting in failure to reject the null hypothesis. Evaluating the bootstrap distribution in Figure 11 it is clear that 73% of randomly generated portfolios performed in excess of P1. The results of the bootstrap analysis correspond with the lack of a consistent relative trend observed in the graphical time-series analysis.

Statistical analyses (the Wilcoxon signed-rank test) of the monthly returns of P1 and the JSE ALSI also failed to reject the null hypothesis, supporting the observations of the graphical time-series analysis and the results of the bootstrap analysis.

The failure of P1 to outperform the market is not surprising given that P1 was the second worst performing portfolio (Figure 8). P2 was the top performing portfolio under the FF5 model and displayed a CAGR of 17.9%, which is below the 18.1% displayed by P1 under the JSE12 model. The results indicate that following a high alpha investment strategy under the FF5 model is not a successful method for outperforming the market.

6.3.3 Conclusion: Hypothesis 2

Under both the JSE12 model and the FF5 model, a portfolio constructed from the highest alpha shares failed to significantly outperform the market. Unlike the FF5 model, this portfolio outperformed the market under the JSE12 model, but bootstrap analysis showed that this outperformance could be attributed to chance in 13% of cases. Statistical tests confirmed that the outperformance displayed by the portfolio under the JSE12 model was not significant at the 0.05 level. In contrast to international alpha based studies which utilised a market neutral portfolio, the failure of the portfolio to significantly outperform the market may be attributable to the loser portfolio driving performance in a market neutral portfolio.

6.4 Hypothesis 3

Hypothesis 3 was concerned with the difference in performance between a portfolio constructed from the lowest alpha value shares and the market. P5 represented a portfolio constructed from the lowest alpha value shares while the JSE ALSI represented the market. The null hypothesis stated that P5 outperformed or performed equally to the market.

Numerically, under the JSE12 model, P5 was comprised of shares with a mean alpha value of -2.62% and never exceeded an alpha value of -0.39% (Table 2). Under the FF5 model, P5 was comprised of shares with a mean alpha value of -1.95% and never exceeded an alpha value of 0.40% (Table 2).

6.4.1 JSE twelve factor model

P5 consistently underperformed the market displaying a CAGR of -5.1% in relation to the market (Figure 6). The persistent downward slope in the price relative, over the duration of the study, was indicative of significant underperformance by P5 in relation to the market.

Figure 4 shows the upper and lower significance bounds of 100 random bootstrap portfolios. The 10.4% CAGR achieved by P5 was below that of all 100 random portfolios (Figure 5) indicating that the underperformance of P5 in relation to the market could not be attributed to chance. The results of the bootstrap analysis were therefore consistent with the graphical time-series observations. The returns from the lowest alpha portfolio (P5) were thus significantly less than returns generated by the market.

Finally, statistical analyses, in the form of the Wilcoxon signed-rank test, of the monthly returns of P5 and the JSE ALSI confirmed the rejection of the null hypothesis.

6.4.2 Fama-French five factor model

Figure 12 shows the performance spread between P5 and the market, exhibiting a CAGR of -4.9% in relation to the market. As with the JSE12 model, the persistent downward slope in the price relative was indicative of significant underperformance by P5 in relation to the market.

The results of the bootstrap analysis were consistent with the graphical time-series observations. Figure 10 shows the upper and lower significance bounds of 100 random bootstrap portfolios in relation to all of the FF5 model portfolios. The 10.7% CAGR achieved by P5 was below that of all 100 random portfolios (Figure 11) indicating that the underperformance of P5 could not be attributed to chance.

Finally, statistical analyses, in the form of the Wilcoxon signed-rank test, of the monthly returns of P5 and the JSE ALSI confirmed rejection of the null hypothesis.

6.4.3 Conclusion: Hypothesis 3

Significant underperformance by P5 in relation to the market was observed under both the JSE12 and FF5 models. Bootstrap analysis showed that in 100 random instances, the JSE ALSI never underperformed P5 under either model. This is similar to the findings of Chong et al. (2017) who noted much lower returns associated with the lowest alpha value portfolio in comparison to all other portfolios. While care needs to be taken when drawing comparisons across different time periods, the case for alpha as an indicator of underperformance appears strong. The CAGRs of 10.4% and 10.7% achieved under the JSE12 and FF5 models respectively are below the worst performing quintiles for liquidity, cash-flow-to-price ratio, price-to-book ratio, net asset growth, interest cover, return-on-equity and return-on-capital styles, as observed by Muller and Ward (2013) on the JSE between 1985 and 2011. Mean alpha levels associated with P5 were -2.62% and -1.95% under the JSE12 and FF5 models respectively, and investors should bear these levels in mind when constructing investment portfolios on the JSE.

Chapter 7: Conclusion

7.1 Principal findings

The study investigated the behaviour and performance of alpha as an investment style on the JSE, as determined by two models for expected return. The results under the JSE12 model were largely similar to international findings (Chong et al., 2017; Hühn & Scholz, 2018) and a significant positive association between alpha and performance was recorded. The same significant association was also found under the FF5 model, however the graphical time-series analysis showed that, using the FF5 model, the association largely disappeared in the higher quintile portfolios after 1998, while the lowest quintile portfolio continued to perform as expected throughout the study. The outcome of the study shows that alpha is a feasible investment style on the JSE. However, the model used to price assets and determine alpha was an important factor in the strength of the style, and it is important to take account of local factors that have a bearing on investment outcomes at a regional level, when selecting a model to price assets.

The results from the highest alpha value portfolio found no evidence to suggest that following a high alpha investment style was a means to significantly outperform the market in South Africa. However, significant underperformance in relation to the market was observed in the bottom quintile portfolio under both models on the JSE, echoing the performance characteristics associated with low alpha shares on US exchanges (Chong et al., 2017). This behaviour provides a useful indicator to stock pickers and investment managers in South Africa.

7.2 Implications for stakeholders

Academically, the study provides additional insight into style-based investment strategies on the JSE. It also provides valuable new information about the performance properties associated with JSE listed shares. Most notably, low alpha value shares consistently and significantly underperform the market. This is of great value to investors and fund managers who should take this behaviour into account when constructing investment strategies and portfolios on the JSE.

7.3 Limitations of research

The study investigated the behaviour of alpha under only two models for expected return: the JSE12 and FF5 models. As the results showed, the performance of the individual portfolios was different under different models, and the application of further models may result in further differences. Thus, the findings of this study are only applicable to the two models in question.

The study did not take into account the effects of transaction costs associated with portfolio rebalancing. Transaction costs were assumed to be more or less equal between portfolios and would thus not influence the relative performance between portfolios. In terms of absolute performance, while transaction costs would not increase P1's performance in relation to the market to a significant level, transaction costs would have an effect on an investor following a short strategy in low alpha shares.

The study was limited to the largest 160 JSE listed companies making up the JSE ALSI. The results may not be applicable to very small capitalisation shares falling outside of this. Further, the results are specific to the JSE and may not hold true on other stock exchanges.

The South African economy is a developing economy and since 1985 it has evolved greatly. Linked to this development, the JSE itself has evolved over this period. Historically, mining has been a very important sector but in the last two decades sectors like banking and financial services, telecommunications, and software and computer services have become relatively more important. It is possible that these changes in the composition of the JSE ALSI over the time period of the study impact on both returns and the determinations of alpha which would affect the results obtained in this study.

7.4 Suggestions for further research

The study found different portfolio behaviours associated with different models for estimating expected return. The research could be extended to examine the JSE results under additional models for expected return such as the CAPM, Fama-French three factor model and Carhart four factor model. Similarly the scope could be extended to investigate the behaviour of the JSE12 model on US markets.

In light of the significant underperformance observed in P5 it would be interesting to evaluate the performance of a short strategy incorporating low alpha shares, including transaction costs, and compare this to the performance of the JSE ALSI.

As discussed in Chapter 6, a downward slope was observed in relative performance during two prominent bear market periods. The study could be expanded to investigate the behaviour of alpha under different macro-economic conditions such as bull and bear market periods.

Finally the alpha investment strategy could be expanded on in future studies by evaluating a combination strategy that makes use of a market neutral portfolio, formed by buying P1 and selling P5.

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Appendix A

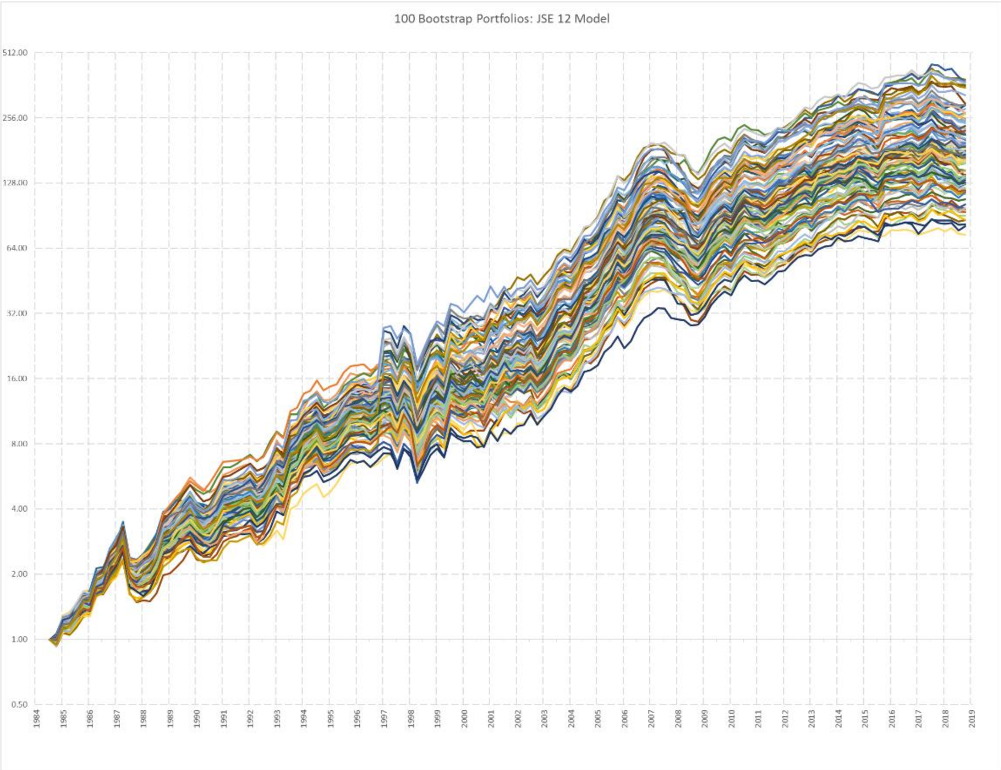

Figure 13: 100 random bootstrap portfolios: JSE12 model

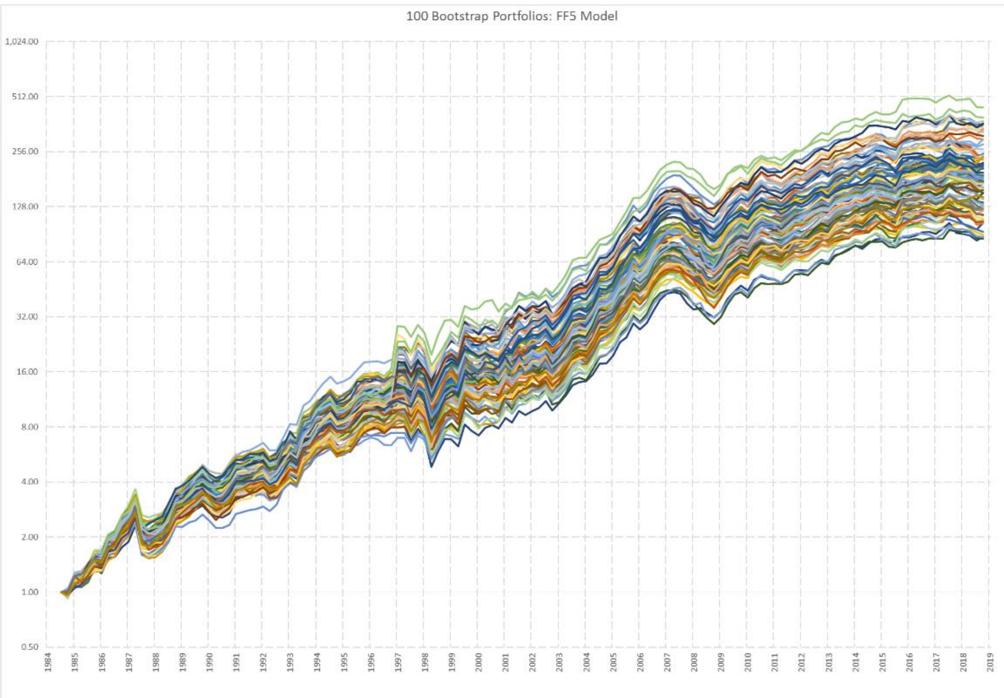

Figure 14: 100 random bootstrap portfolios: FF5 model

Appendix B – Ethical clearance

Gordon
Institute
of Business
Science
University
of Pretoria

01 July 2019

Sean Fielding

Dear Sean

Please be advised that your application for Ethical Clearance has been approved.

You are therefore allowed to continue collecting your data.

Please note that approval is granted based on the methodology and research instruments provided in the application. If there is any deviation change or addition to the research method or tools, a supplementary application for approval must be obtained

We wish you everything of the best for the rest of the project.

Kind Regards

GIBS MBA Research Ethical Clearance Committee