Research Report

The Volatility Factor and the Alpha of Hedge Funds and Mutual funds in South Africa.

ONAINDINI SANYANGARE: 670143
SUPERVISOR: PROFESSOR ODONGO KODONGO

Thesis submitted in fulfilment of the requirements for the degree of
Masters of Management in Finance and Investments in the
FACULTY OF COMMERCE LAW AND MANAGEMENT
WITS BUSINESS SCHOOL
at the
UNIVERSITY OF THE WITWATERSRAND

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Abstract

Performance measures based on CAPM, such as Jensen's (1968) alpha, with alpha measuring the value addition or outperformance by portfolio fund managers relative to the market or comparable benchmarks, have been used to measure or assess portfolio manager skill or performance. Assessing fund manager performance is crucial to the investment process, and it assists with decision making (Andrew, 2014). Research is limited when looking at the South African context and considering the performance of both fund management sectors while incorporating the low volatility-anomaly. This study sought to determine if volatility is priced in the South African hedge funds and mutual funds. This was achieved through the application of multifactor asset pricing models and Jensen’s Alpha. Some perivious stduies have identified this anomaly and found that portfolios with low volatility of returns outperformed their significant-high volatility counterparts. This study uses the Carhart (1997) model and the Fung and Heish (2001) models augmented for volatility to determine if volatility is indeed priced in South Africa’s mutual fudns and hedge funds. First, the hedge fund and unit trust returns were modelled without the volatility factor, and secondly, the returns were modelled factoring in the volatility factor. This was done to demystify the impact of the inclusion of the volatility factor, particularly to the alphas, and to separately capture the impact of the volatility factor on the overall returns of the unit trusts and hedge funds in South Africa. Although insignificant in most of the models, the inclusion of the volatility factor did improve the explanatory power of the models.

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Chapter I: Introduction and Background

1.1 Introduction

Investors are concerned with the performance of their investments. Depending on their investment goals, investors need to asses if their assets or portfolios will be sufficiently managed, thereby ensuring that their objectives are realized. Assessing fund manager performance is crucial to the investment process, and it assists with decision making (Andrew, 2014).

Performance measures based on CAPM, such as Jensen's (1968) alpha, with alpha measuring the value addition or outperformance by portfolio fund managers relative to the market or comparable benchmarks, have been used to measure or asses portfolio manager skill or performance. Actively managed funds seek to outperform the benchmark and generate positive alpha; accurately measuring the presence, or lack thereof, of alpha, is essential to the investment process.

In South Africa, the hedge fund and mutual fund industries have grown substantially. With this growth, it is essential to measure performance adequately. Studies have been done that assess performance or skill in both sectors in the South African context (see Botha, 2007; Mibiola, 2013; Tan, 2015; Momoza, 2017; Adenigba, 2017; and Kunene, 2017). Research is limited when looking at the South African context and when considering the performance of both industries while incorporating the low volatility-anomaly.

1.2 Background/Context

The volatility of returns, or the past volatility, is considered an important factor when evaluating the performance of mutual funds. Empirically, portfolios with lower volatility of returns have been seen to outperform their more volatile counterparts (see Haugen & Heins, 1972; Haugen & Baker, 1991; Baker & Haugen 2012; and Blitz, Pang, & Van Vliet, 2013). This phenomenon has been referred to as the low volatility anomaly. Thus, the low volatility anomaly has been defined in the literature as the persistence of low volatility stocks outperforming high volatility stocks (see Baker, Bradley & Taliaferro, (2014).

The low volatility anomaly is characterized by a negative relationship between risk and return: for example, Haugen and Heins (1972) documented a negative correlation between risk and return over 45 years beginning in 1926. Other empirical studies that have identified the persistence of low volatility stocks outperforming high volatility stocks include Baltussen, Bekkum, and Grient (2014); Novy-Marx (2016) and Driessen, Kuiper, Nazliben, and Beilo (2019).

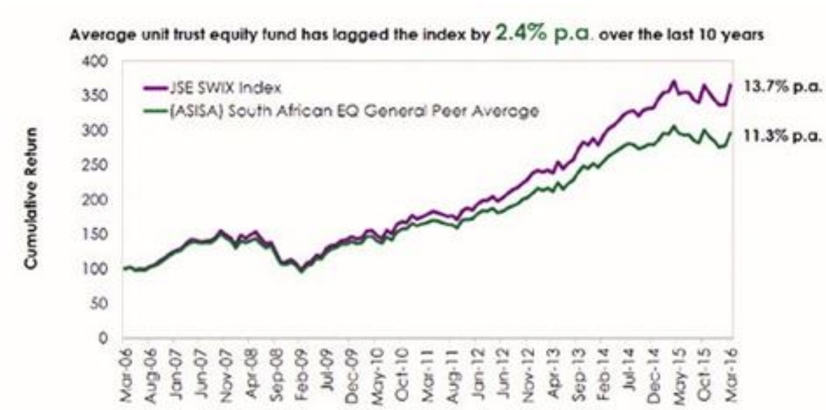
The persistence of the volatility anomaly has also been identified in emerging markets around the world: Blitz et al. (2013) examined the presence of the volatility anomaly in 30 countries, including South Africa, and documented its strong presence. In South Africa, studies such as Khuzwayo (2011), Panulo (2014), and Oladele and Bradeld (2016) have also identified this anomaly and found the portfolios with low volatility of returns outperformed their significant-high volatility counterparts. Given the persistence of this anomaly, merely observing it is not enough; it is essential to account for the persistence in asset pricing models and performance measures (see Fama & French, 2015; and Jordan & Riley, 2015).

According to Price Waterhouse Coopers (2017), the total global assets under management in the investment industry are expected to grow from US$84.9 trillion in 2016 to US$145.4 trillion by 2025. Accurately and adequately measuring performance is essential in this growing industry. Mutual funds and hedge funds globally contribute a substantial amount to the global investment industry, precisely measuring their performance impacts on the decision making of both retail and professional investors.

Mutual funds and hedge funds pool funds from investors and are both professionally managed. Globally, they account for a large percentage of assets under management. While mutual funds pool funds from a diverse pool of investors, hedge funds generally cater to high net-worth individuals. Hedge funds are offered to investors as private investment partnerships. Portfolio managers for both hedge funds and mutual funds charge management fees and costs relative to the funds in question; in addition, hedge funds also have incentive-based payment structures relative to profits or absolute returns.

Mutual Funds : Historians are unclear about the exact origins of mutual funds; however, the first modern-day mutual fund, named Massachusetts Investors Trust, was established in 1924 in the United States of America; the fund grew to US$ 392,000 in just one year (The Investment Funds Institute Canada, 2019). The industry has expanded since then, with a total of US$ 75.75 trillion in 2016 (The Investment Funds Institute Canada, 2019), accounting for 71% of the total global assets under management.

Figure 1 Average Unit Trust Performance



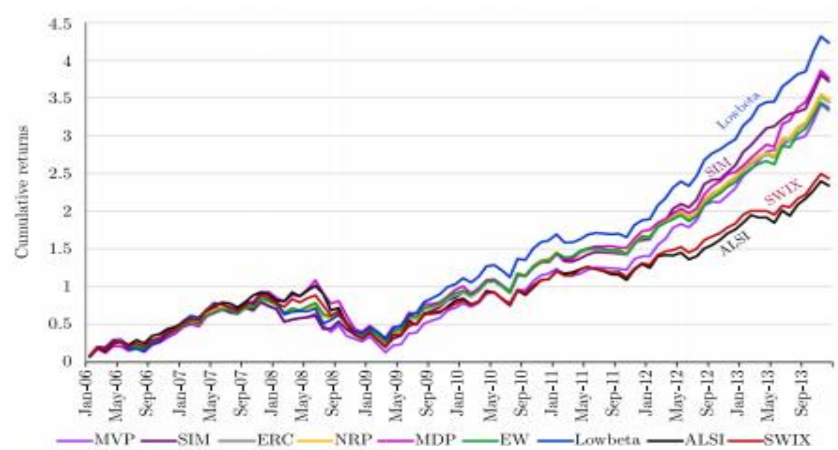
Source: (Insurance Gateway South Africa, 2017)

Mutual funds cater to different types of investors with varying net-worth, investment goals, and needs. They have different risk-reward profiles, areas of investment, costs, and they have objectives that are tailored to the fund's assets. Mutual funds can either be passively or actively managed. With active management, the portfolio manager aims to beat the market or any related identified benchmark. However, with passive management, the portfolio manager selects assets designed to track the performance of the market or any relevant identified benchmark. The cost and fees depend on the type of fund with actively traded funds attracting higher costs than their passively managed counterparts (Lioudis, 2019). Actively managed funds account for USD$ 60.6 trillion of global assets under management (PWC, 2017).

Mutual funds or Unit Trusts, as they are referred to in South Africa, originated in 1965, with an asset value of ZAR 600 000 or US$ 41 902 thousand (Meyer-Pretorius & Wolmarans, 2006) with the industry growing to ZAR 2 trillion or US$ 139,685.33 million.

Mutual funds (or unit trusts) are closely monitored and regulated by the Financial Sector Conduct Authority under the *Collective Investment Schemes Control Act No. 45 of 2002.* Following the global trend, actively managed funds dominate in the unit trust or mutual fund investment industry. Of the ZAR 2 trillion assets under management in the mutual fund industry in South Africa, 80% are actively managed. There are 1,171 unit trusts in South Africa. Figure 1 illustrates the performance of South African Unit Trusts relative to the JSE SWIX Index[1]; over ten years, unit trusts have lagged behind the index. The general peer average over ten years was 11.3% per annum relative to an index return on 13.7%, a difference of 2.4% per annum.

Figure 2 Low Volatility Portfolio Performance South Africa



Source: (Oladele and Bradeld, 2016)

Key – Figure 2 (Minimum Variance (MVP), Low Volatility Single Index Model (SIM), Equal Risk Contribution (ERC), Naïve Risk Parity (NRP), Maximum Diversification (MDP), Equal Weighting (EW), Shareholder-Weighted Index (SWIX) ALSI (the market capitalization-weighted benchmark)

Looking at a sector-based study by Oladele and Bradeld (2016), the low volatility portfolios in South Africa outperformed the market benchmark; adding low volatility portfolios also improved overall portfolio performance. Figure 2 illustrates evidence from the study showing low beta portfolios and their cumulative performance over *seven years.*

[1] Shareholder Weighted Index (SWIX) components are weighted based on the shareholders' share capital registered on the South African share register in a dematerialized form.

Hedge funds :The first hedge fund was established in 1949 by a financial journalist in the United States of America, raising $100 thousand to offset risk by holding various positions in stocks (Chen, 2019). Hedge funds use alternative investment strategies and have grown to presently manage $US 2413 billion worth of assets (PWC, 2017). Since the first hedge fund in South Africa was established in 1995, the industry has grown to end 2017 with ZAR 62.40billion or the US $4.36 billion in assets under management (ASISA, 2018).

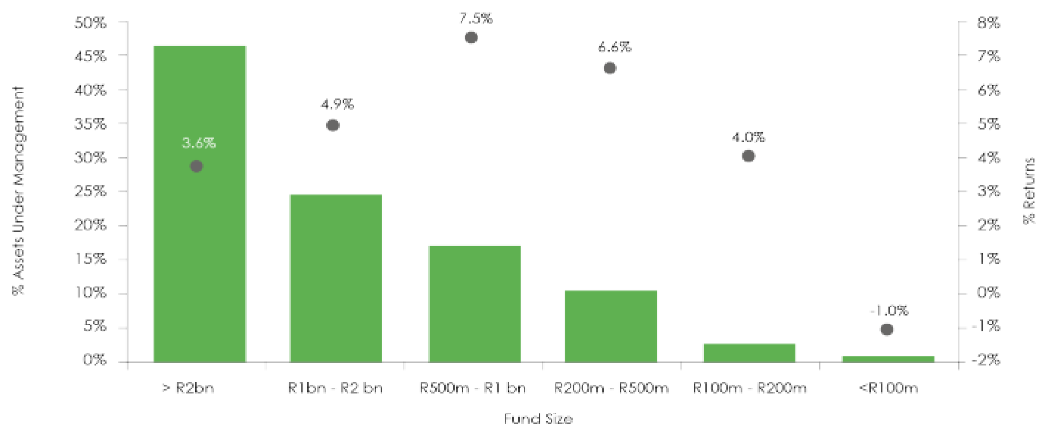
Hedge funds utilize different strategies that aim to earn active returns for their investors relative to a benchmark or the market while shielding against market risk (Fung & Heish, 1997). Hedge funds are generally accessible to professional or accredited investors. In South Africa, however, hedge funds are available to both retail and professional high net worth investors. Similar to mutual funds, hedge funds in South Africa are carefully regulated and monitored by the Financial Sector Conduct Authority *under the Collective Investment Schemes Control Act No. 45, 2002*. The act groups hedge funds in South Africa under two categories:

- Retail Hedge Funds (RIFs) - Ordinary retail or smaller investors can invest in these funds; the funds have no minimum investment amount;
- Qualified Investor Hedge Funds (QIFs) – Qualified large investors can invest, and a minimum investment amount of ZAR 1 million or USD$ 69716.29 applies.

This regulation aims to promote transparency and investor protection in South Africa. According to Novare (2017), under this new regulation, there were a total of 295 registered hedge funds in South Africa. In 2017, hedge funds in South Africa had a total ZAR 62.4billion worth of assets under management. Assets are managed to utilize the following investment strategies that are common to the South African Hedge Fund Industry, namely, equity long/short, equity neutral, fixed income, statistical arbitrage, volatility arbitrage, and multi-strategy strategies. The definitions of these strategies can be found in Appendix A.

Figure 3 looks at the hedge fund industry in South Africa per the size, returns and assets under management, the green bars represent the percentage of assets under management relative to the fund size in the hedge fund industry; the dots represent the returns attributable to the fund sizes. Returns in 2017 ranged between -1% and 7.5%, with relatively medium-sized funds (7.5% and 6.6%) performing better than the larger funds. Over the same period (12 months leading to June 2017), the All Bond Index, The All Share Index, and Cash returned 7.9%, 1.6%, and 7.6% respectively, according to Novare (2017). The more inferior returns may be attributed to the turbulent economic and political environment in South Africa during the period.

Figure 3 Hedge Fund Performance in South Africa



Source: (Novare Hedge Fund Survey, 2017)

Key - Figure 3
Green – Assets under management, fund size.
Black – Percentage returns attributable to the fund size

Figure 4 illustrates the performance of hedge fund strategies in South Africa. Under the new regulations of the hedge fund industry, there are 295 hedge funds with 70% of assets under management in the qualified investor category and 30% of assets under management attributable to the retail investor category. According to ASISA (2018), the most popular hedge fund strategy in South Africa is the equity long-short: in 2017, 69% of assets under management were allocated to this strategy. The top-performing strategy in 2017 was the Fixed Income strategy, to which can be ascribed 14.1% of assets under management in the industry.

Looking at Figure 4, Market Neutral Strategies and Equity Long-short Strategies had more substantial downside returns when compared to the other strategies, the significant downside returns indicate the risks associated with hedge fund expected returns in the South African Context. Figure 5 illustrates the hedge fund index weighted performance relative to the FTSE/JSE All-Share Index: an upward trend in returns can be observed on the graph with the All-share Index outperforming the different strategies at different times. Hedge fund strategies are more complex and carry a high degree of risk.

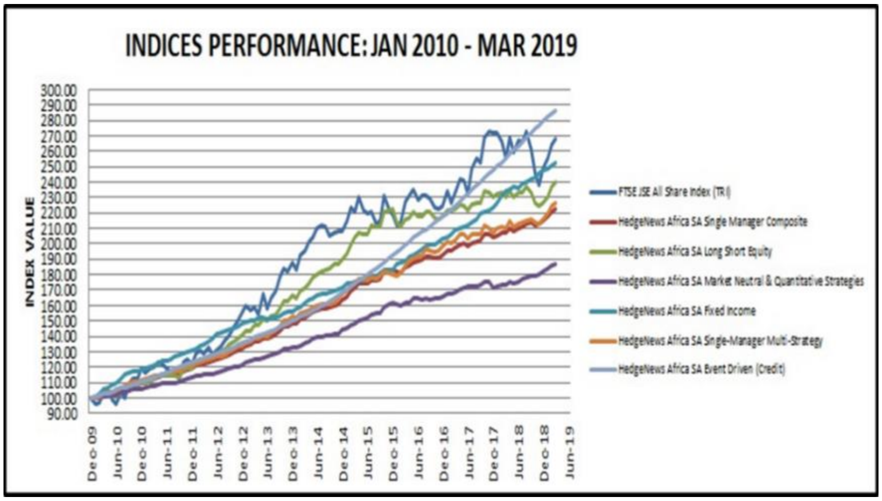
Figure 4 Hedge Fund Performance in South Africa - Strategies

Key – Figure 4
Green – Return distribution for fund strategy in 2017
Black – Average return per strategy

Source: (Novare Hedge Fund Survey, 2017)

As shown in figure 4, the equity long/short and market-neutral strategies had the most considerable downside risk and the lowest returns in 2017. Fixed income strategies exploit pricing inefficiencies in fixed income or bond markets. Bonds are often less volatile than equity; however, this alone is not the sole determinant of hedge fund volatility in the fixed income category. Managers can invest in low-grade bonds based on perceived pricing anomalies, which typically carry higher risk. Multi-Strategy hedge funds allocate capital across different strategies, which reduce exposure to a single approach.

Figure 5 Hedge fund indices performance - South Africa



Source: (HedgeNews Africa, 2019)

As shown in Figure 5, the indices of performance over nine years indicate that market-neutral strategies and quantitative strategies have underperformed in comparison to the other strategies. The FTSE/JSE All Share Index event-driven strategies have outperformed the different strategies, and exceeded the benchmark index, from December 2018 to April 2019. The fixed income strategy underperformed relative to the equity long-short strategy but performed better than the equity long-short strategy from December 2017 to April 2019. The volatility of hedge fund returns is based on several factors, such as the amount of leverage used when executing strategies.

1.3 Statement of the Research Problem

In finance, accurate performance evaluation is an area of importance to investors and fund managers alike. It is critical for performance to be measured with precision. In the literature, the low volatility anomaly has been observed empirically (Haugen, & Heins, 1972; Baker, 1991; Baker & Haugen, 2012; Blitz et al., 2013). Failure to accurately account for this anomaly can lead to an erroneous valuation of fund managers' skills and performance (Jordan & Riley, 2015).

The purpose of this study is to investigate the effects of the volatility of returns on performance measurement in the hedge fund and mutual fund industries in South Africa. The two industries have grown substantially and so has the need to adequately measure performance; both investors and fund managers require accurate performance measures in order to justify the fees and expenses paid to the various funds (Satchell & Farah, 2002). In South Africa, there is no clarity on how fund-level volatility affects the performance of hedge and mutual funds or how investors need to incorporate volatility arising from managers' portfolio choices in evaluating fund performance.

The presence of the low volatility anomaly has also been evidenced in emerging markets (Baker & Haugen, 2012; Baker & Haugen, 2013; and Blitz et al., 2013). In South Africa, Oladele and Bradeld (2016) found that low volatility portfolios outperformed the market capitalization-weighted index.

When looking at the relationship between hedge fund performance and market volatility, Momoza (2017) found that index or market volatility had limited explanatory power when applied to the hedge fund strategies in South Africa. Index volatility is not directly related to the volatility of individual portfolios. Contrarily, Blitz (2018) found that although the volatility anomaly was significant when predicting hedge fund returns, the coefficient (sensitivity factor) of the low volatility-factor was negative, suggesting that hedge funds have negative exposure to the low volatility- factor[2] (Blitz, 2018).

[2]. A negative exposure to the low-volatility factor implies that hedge funds are not exposed to the low volatility anomaly. Hedge fund portfolios are exposed to assets with the high volatility of returns.

1.4 Research objectives

This study aims to examine the volatility of returns as a determining factor of the performance of mutual funds and hedge funds through the application of an augmented Capital Asset Pricing Model. The specific objectives of this research are:

1. To ascertain whether volatility is priced in mutual fund and hedge fund returns in South Africa;
2. To establish the relationship between the volatility factor and the performance of the mutual fund and hedge fund managers.

1.5 Research Questions

I. Is the volatility of returns a significant determinant of expected returns on hedge funds and mutual funds in South Africa?

II. How does the volatility factor inform the performance of the mutual fund and hedge fund managers?

1.6 Significance of the study

The South African hedge fund and mutual fund industries are relatively small and young when compared to similar industries in the United States and other advanced markets. However, the mutual funds and hedge funds industries are growing, making it essential to have a better understanding of the factors that influence returns. In particular, this study assesses the volatility of returns and their impact on performance measurement tools relevant to financial industry practitioners and investors, both retail and professional. Knowledge of the relationship between volatility and return in these industries is still minimal; this study seeks to explore the linkage and to proffer informed guides to investors and fund managers.

Chapter II: Literature Review

2.1 Factor Asset Pricing Models: Portfolio Evaluation

2.1.1 CAPM and Multifactor Models

The capital asset pricing model (CAPM) was developed in the 1960s by Jack Treynor (1962), William Sharpe (1964), John Lintner (1965), and Jan Mossin (1966) and is based on the efficient portfolio theory.

CAPM is a single factor model that illustrates the relationship between systematic risk (beta) and an asset return. CAPM has been utilized to price and evaluate the performance of portfolios. The single factor CAPM suggests that return on an asset comprises of the time value of money (risk-free rate) and systematic risk (market). The single factor capital asset pricing model (CAPM) identifies the relationship between systematic risk and asset returns. Empirical evidence, however, suggests that a single factor isn't enough to capture asset returns. Multifactor CAPM models such as Fama and French (1993), Carhart (1997), and Fama and French (2015), which capture anomalies of the nature discussed in this thesis, have been shown to improve the performance of the single-factor model. Majority of studies centered on CAPM and multifactor models have been centered around developed economies and emerging markets such as Asia and Latin America (Alagidede, 2011)

An alternative to CAPM is the Arbitrage Pricing Theory (APT), which was developed by Stephen Ross (1976), is a linear factor model similar to CAPM. The APT is similar to the CAPM model; however, it makes three assumptions, namely that asset-specific risk is eliminated through diversification, models fully explain returns, and no-arbitrage opportunities exist.

Fama and French (1993) proposed a three-factor that expands on the existing single-factor model by adding two empirical factors, namely "small minus big" factor (SMB) which accounts for a size premium; and the "high minus low "factor (HML) which accounts for a value premium. The addition to this model is the Carhart (1997) model, which extends the three-factor model by adding a momentum factor. The momentum effect looks at how stocks tend to follow a specific price trend based on performance from the previous year.

Fama and French (2015) suggested that the three factors were incomplete and did not account for variation attributable to the relationship between expected return and its connection with profitability and investments. Thus, Fama and French (2015) expanded on the Fama and French (1993) by adding two new factors, namely profitability and investments of firms. The profitability factor or the "robust minus weak" (RMW) is the difference between stocks with robust profits and stocks with weaker profits. The investment factor or "conservative minus aggressive" (CMA) is the difference between returns on stocks that invest conservatively and stocks that invest aggressively.

In literature, a variety of models have been used to assess the performance of hedge funds and as a result, studies have yielded different results Eling and Faust (2010). Performance measures were required to adequately capture the different styles and strategies employed by hedge fund manager (Fung and Hsieh, 2001; Fung and Hsieh, 2004; Agarwal and Naik, 2004). Fung and Hsieh (2001) suggested that due to the complexity of hedge fund strategies, the capital asset pricing model did not explain hedge fund returns adequately. A seven-factor model based on the Arbitrage pricing theory was developed. The seven-factor model had factors based on trend following, bond trends, and equity trends. The seven-factor model aimed to capture or explain the returns of a well-diversified hedge fund portfolio.

2.1.2. Fund Performance and Multi-Factor Models

CAPM and multifactor models can be used in the performance evaluation of fund manager skills. A performance measure that was developed from the CAPM single-factor model is Jensen's (1968) Alpha. Performance measures were developed from CAPM, such as Jensen's Alpha (1968), which captures a portfolio excess returns or alpha (α) relative to a benchmark. Jensens Alpha is a commonly used performance measure in industry and is utilized to measure skill and value addition of portfolio managers. Berk and Binsbergen (2015) identified that investors injected more capital into high performing funds, and better performing funds earned higher fees.

Multifactor benchmarks have become increasingly popular in literature for measuring the performance of funds (see, Carhart, 1997; Fama & French, 1993; Fung & Heish, 2001; and Fama & French, 2010). The presence or absence of alpha can be effectively utilized to evaluate manager performance. "The basic economic principle of rents holds that someone cannot earn a "rent" — a wage above costs, in this case — unless they possess the desired skill in short supply." Fund managers earn high salaries based on this skill, which has been historically measured by alpha.

2.2 Volatility Factor

Risk is a significant input in any financial market, and a widely accepted measure of risk is the volatility; failure to account for this either directly or indirectly when assessing active portfolio managers can result in an overestimation of portfolio manager skill.

Haugen and Heins (1972), Haugen and Baker (1991), and Baker and Haugen (2012) demonstrated historical evidence from financial markets which illustrated that portfolios with lower volatility tend to outperform portfolios with higher volatility. This pricing anomaly had been observed further in the literature (see Clark, de Silva, and Thorley (2011); Baker and Haugen (2012); Novy-Marx (2016). The presence of the low volatility anomaly had been identified in different financial markets around the world. Incorporating the volatility anomaly factor in performance measures improves the explanatory capacity of the model.

Fama and French (2015) argued that the five-factor model could explain the volatility anomaly with the introduction of two new factors, namely profitability and investment. Jordan and Riley (2015) accounted for the volatility anomaly by directly introducing a volatility factor to the four-factor Carhart (1997) model. They further accounted for the volatility anomaly indirectly by adding the profitability and investment factors from the Fama and French (2015) to the four-factor model, and in both instances', alpha was both statistically and economically insignificant. The introduction of the volatility factor, either directly or indirectly, can potentially improve the accuracy of the measurement of the skill of fund managers.

2.3 Mutual Funds

2.3.1 Mutual Funds: Active Management vs. Passive Management

A mutual fund pools money from several different investors and then purchases assets or securities. Mutual funds can either follow an active or passive investment style. Active fund managers aim to outperform the market; in effect, actively managed funds seek to generate returns above the market or positive alpha. Jensen (1968) addressed the question of portfolio performance between the different investment styles and found that, on average, actively managed funds do not outperform the market, sparking a debate in the literature.

Actively managed funds attract more costs when looking at management fees and expenses. An important question that has been discussed in the literature is whether or not active mutual funds have the ability or skill to outperform the benchmark or the index (see, Hendricks, Patel, & Zeckhauser, 1993; Fama & French, 2010; and Doshi, Elkamhi & Simutin, 2015).

Berk and van Binsbergen (2015) found that, on average, average mutual funds utilized their skills to generate millions of dollars every year, and investors are attracted to, and reward, this skill or rather the benefits attached to this skill. Funds with better performance are awarded more capital, and as performance increases, so do the management fees of the funds. Fama and French (2010) stated that the costs that was associated with active management was high and affected the actual returns of investors. In the study, they found that very few funds produced adequate returns to cover the costs that were associated with active management.

Cuthbertson, Nitzsche, and O'Sullivan (2004) further stated that it was more useful for investors to invest in passive or indexed managed funds due to the high costs associated with actively managed funds. Investors, however, continued to put capital in actively managed funds, and there are also a significant number of actively managed funds in existence, which suggests that there may be possible benefits associated with an investment in actively managed mutual funds. The focus of this study, was to provide a review of the empirical findings on the performance of mutual funds in the US and UK markets over a fifteen year lifespan. The authors also reviewed various models and performance measures available across literature. The reviewdid not consider studies conducted in emerging markets, and if the various models and performance measures were effective or yield the same results as developed markets.

2.3.2 Mutual Funds: Performance

Some literature suggested that actively managed mutual funds rarely outperform the benchmark or passively managed funds, Carhart (1997) argued that after adjusting for exposures to known risk factors, abnormal returns were small or non-existent. Malkiel (1995) found that after deducting expenses and costs, a significant number of mutual funds underperformed the market. Fama and French (2010) fowarded that when the costs of active management are deducted in the composition of return, very few funds could produce benchmark expected returns that were sufficient enough to cover these costs. The study added back the costs or fees associated with the funds, and little evidence of performance or alpha relative to the benchmark was identified, in aggregate, funds underperformed the benchmark.

Wermers (2000) found that the average mutual fund underperformed passively managed funds when net returns were considered. In addition, French (2008) postulated that after expenses and fees investors could increase their returns by investing in passive funds, the cost of investing in actively managed funds was substantial and would erode returns. Bu and Lacey (2014) found that only a small percentage of the actual funds held and the control group earned positive abnormal returns. The study assessed mutual fund manager skills in the US against controlled bootstrapped funds[3]; manager skill was then examined based on outperforming probability and the cumulative distribution[4]. The authors also assessed the funds based on their risk and return trade-off, funds with a

[3] The bootstrapped funds are formed through random selection and replacement each month.
[4] The study does not make any assumptions about the distribution and performance of the bootstrapped funds.

higher return per unit risk were more efficient and manager skills exist, the authors also control for age. Moreover, the study did not consider the fund specific factors that influenced the outperformance or lack thereof. Wermers (2000) decomposed the returns of mutual funds in attempt to identify which fund characteristics had a high correlation with positive high returns. Funds with a high turnover outperformed the selected index. This was in contrast to the findings of Carhart (1997), turnovers and expense ratios were found to be negatively correlated to returns.

Hendricks et al. (1993) found that mutual funds that were performing well tend to perform well in the short run. However, Carhart (1997) attributed this performance of exposure to known risk factors. Bollen and Busse (2004) tested for the persistence of performance in mutual fund performance, it was found that persistence in performance in the short run did exist, but this persistence was not observed in the long term. Grinblatt and Titman (1992) assessed the persistent performance of mutual funds and found that past performance was related to future performance, and persistence does exist. In their study, persistence in performance was attributed to the skills of the portfolio managers and other factors.

Kremnitzer (2012) found that actively managed funds did outperform passively managed funds before and after taxes in the emerging market. The author specifically looked at both mutual funds and ETFs as a representative of active and passive funds respectively. Moreover, the study focused on emerging market mutual funds and equity funds available in the United States market only over a short period of three years. The funds in question can have holdings in the following regions; Asia Pacific, Latin America Emerging Europe and Middle East and Africa. The funds can also hold investments in developed markets. In contrast, this study focuses specifically on mutual funds and hedge funds in South Africa and considers a longer time period. In Doshi et al. (2015), the study assessed active mutual fund skills and found that highly active funds performed better than less actively managed funds. Ferson and Mo (2016) argued that the performance of mutual funds was dependent on their skills, such as stock picking, market timing, and volatility timing. In the study, it was found that some funds do exhibit stock picking and market timing ability. Grinblatt and Titman (1992) also found that mutual funds persistently observed abnormal returns, and the persistence can be attributed to the fund managers' skills; the study utilized a single factor CAPM to assess performance.

Multifactor models have been empirically observed to perform better than the single factor CAPM. In a follow-up study, Daniel, Grinblatt, Titman, and Wermers (1997) found that funds exhibit skills when looking at selectivity but not market timing. Portfolios in the study where compared to a benchmark of passively managed portfolios. Berk and Van Binsbergen (2015) found that skills in fund managers do exist. Still, it cannot be found through alpha, but rather through the value-added, the study argued that mutual fund skill can be more accurately measured when it considered the value the fund generates from the market, its gross return and its benchmark.

Cuthbertson et al. (2004) found that stock-picking skills did exist and that a lack of performance could be attributed to a lack of skill. However, it was also atticulated that abnormal performance in funds could also be attributed to luck. The authors further argued that the evidence of skill and the evidence of luck could indicate that investors cannot adequately measure performance. Ding and Wermers (2009) realised that outperformance relative to a benchmark could be observed in large funds, whilst experienced small fund managers do not outperform their respective benchmarks. The authors examine three performance measures with use of the Carhart (1997); the first measure excluded the expense ratio, the second measure included it. The third measure was based on characteristic selectivity. The study examined performance of US mutual funds and the role of fund boards.

Mutual funds generated millions of dollars every year based on their skills (Berk & Van Binsbergen, 2015); better-performing funds were allocated more capital, and as performance increased, so do management fees and costs. Some studies have found evidence of persistence of performance of active mutual funds, while others found no evidence and argued that the actively managed fund rarely outperformed their benchmarks and the costs associated funds negatively impact returns (Malkiel, 1995; Carhart,1997; and Fama & French 2010). Evidence of outperformance, however, has been identified but has been limited to the short-run (Hendricks, Patel & Zeckhauser 1993 and Bollen and Busse, 2004). Grinblatt and Titman (1992) examined the skill of managers which was assessed by the ability of managers to time volatility; to time the market and adequately select securities or stocks. Some evidence was found in favor of these abilities and abnormal returns.

Based on empirical evidence, performance, or a lack of performance of mutual funds can be attributed to several different factors. Different performance measures that indicate skill have been utilized in the literature. Skill in the mutual fund industry has been attributed to market timing abilities, security selection abilities, and volatility timing abilities.

Mutual Funds and Performance in South Africa: Studies concerning mutual fund performance in South Africa are scarce. Tan (2015) studied the performance of mutual funds over a five-year and 10-month period. Fourteen South African mutual funds were assessed using the Sharpe ratio, Treynor Ratio, and Jensen's Alpha, the ability to time the market was also tested adequately. The study found that mutual funds did not have a significant selective or timing ability. The study selected 10 mutual funds in South Africa based on selection criteria such as: the percentage of equity shares, fund type and the age of the fund. The study did not consider the performance of mutual funds during the financial crisis from 2007-2008, the study was focused on the quantitative easing policy term from 2009 to 2014. The study also assessed the market timing of managers and does not explicitly considered other skills such as volatility timing.

Manjezi (2008) found that a significant percentage of the South African mutual funds had a significant alpha. The study assessed 15 mutual funds over a five year period and 9 of the 15 funds had above average performance. Similar to Tan (2015), Manjezi (2008) examined the market timing and selection skills of the funds. Both studies conclude that there was little or no significant timing and selection skills in the South African context. Both studies did not consider the market timing abilities and performance of the fund during the financial crisis. Both studies also examined very few funds. Mibiola (2013) assessed unit trusts in South Africa for over twenty years; evidence could not be found in favour of persistence of performance; 64 funds in the general equity category were examined. The study assessed the performance of funds using the Sharpe Ratio and the single factor CAPM. Similar to this study, Mibiola (2013) limits the sample to the South African Equity General category, findings cannot be applied to all the different categories of unit trusts in the South African context. Contrarily this study utilised the Carhart (1997) and further augments the model for the volatility factor . Previous studies have found that the single factor CAPM did not adequately describe returns (see;Fama and French, 1993; Carhart ,1997; and Fama and French 2015).Nana (2012) investigated the performance of mutual funds in South Africa for over ten years; their study was unable to conclusively find evidence that supports the performance persistence of mutual funds in South Africa. The study considered both mutual funds and ETFs in South Africa whilst controlling for funds that had been in existence for 10 years, introducing survivorship bias. The study also assessed the performance of the funds over the full ten year period and two five year periods; this was done to assess performance directly over bull and bear markets. Performance was examined using CAPM, Fama and French (1993), Carhart (1997) and a performance evaluation model by Ferson and Warther (1996)[5].

2.3.3 Mutual Funds: Volatility and Returns

Jordan and Riley (2015) showed that the volatility of historical returns of portfolios and stocks is an essential factor to consider when predicting expected returns on assets and how this volatility impacts the measurement of performance of the portfolio fund managers.

Haugen and Heins (1972) produced a working paper covering 45 years, which addressed the relationship between risk and return and how a negative correlation could be observed between risk and return, stocks with lower volatilities were observed to outperform stocks with higher volatilities. Haugen and Baker (1991) also showed that low-risk stocks have persistently outperformed their higher-risk counterparts. This persistence has been observed by Baker and Haugen (2012) in financial markets around the world. The study

[5] This model aims to account for the dynamic behavior that is exhibited by stock returns.

covered 33 markets over 20 years; of the 33 markets examined, 21 were from developed markets, and 12 were from emerging markets, including South Africa.

Blitz and Van Vliet (2007) also identified the anomaly in the United States, European and Japanese Financial Markets over 20 years, in this study, the portfolios with the lowest historical volatility of returns over three years exhibited returns that were higher than its high volatility of returns counterpart. Blitz et al. (2013), in a follow-up study, found the anomaly in a study concerning emerging markets. Clarke et al. (2011) postulated that the portfolio with a minimum variance outperformed the market over 42 years. The minimum variance portfolio in this study was constructed from the largest 1000 stocks in the United States.

Blitz (2016) demonstrated that there was a distinct and persistent low volatility effect; the study further suggested that the evidence for the low-volatility is as relevant or as reliable as the evidence for the value premium effect. Oladele and Bradeld (2016) assessed low volatility sector-based portfolios in the South African context by constructing minimum variance portfolios with certain constraints. The study found that low volatility portfolios did outperform the market capitalization-weighted index in South Africa. The study assessed different low volatility portfolio construction techniques, and created blended portfolios containing the various sectors and using the Shareholder- Weighted Index as a proxy. The study covered sectors from the FTSE/JSE over a ten year period. In contrast, this study examined the mutual fund and hedge industries.

The volatility anomaly can be attributed to the fact that portfolios or stocks with the high volatility of returns and high betas are more strongly inclined towards smaller growth firms that are less profitable, which explained the underperformance of high volatility stocks or portfolios (Novy- Marx, 2016). Baltussen et al. (2014) showed that the volatility anomaly exited; , the uncertainty of risk was measured by a vol-of-vol factor (volatility of expected volatility) using the implied volatility of options prices. They found that stocks with higher volatility of volatility characteristics had low future returns. This study assessed a sample of stocks over ten years. Driessen et al. (2019), in a recent study, acknowledged the presence of the volatility anomaly. However, they argued that the outperformance of stocks with low volatility of returns can be explained by exposure to the interest rate, with some stocks being more exposed to the interest rate.

2.4 Hedge Funds

2.4.1 Hedge Funds: Strategies

Globally, the assets under management by hedge funds amounted to 2.9 trillion U.S dollars in 2018.

Unlike mutual funds, hedge funds employ many dynamic strategies (Fung and Heish,1997 and Argarwal, Bakshi, and Huji,2009), which enable them to make active returns and to outperform their benchmarks (Boasson and Boasson, 2011).

However, some studies attributed this performance to the stage of the business cycle: performance has been observed persistently following a market downturn (Hsu, Kuan & Yen, 2013; Sun, Wang & Zheng, 2014). Despite this discrepancy, evidence was found that hedge funds did not continuously outperform the market; however, they do outperform mutual funds (Liang, 1999; Ackermann, McEanally & Ravenscroft, 1999).

Hedge fund strategies aims to produce absolute returns irrespective of the market conditions; the different types of strategies employed by hedge funds are illustrated in figure 6.

Figure 6 Hedge Fund Strategies

Hedge Fund Strategies Can be Grouped into Four Major Categories

	Subcategory	Description
Arbitrage	Fixed-income based arbitrage	Exploits pricing inefficiencies in fixed-income markets, combining long/short positions of various fixed income securities
	Convertible arbitrage	Purchases convertible bonds and hedges equity risk by selling short the underlying common stock
	Relative value arbitrage	Exploits pricing inefficiencies across asset classes-e.g., pairs trading, dividend arbitrage, yield curve trades
Event Driven	Distressed securities	Invests in companies in a distressed situation (e.g. bankruptcies, restructuring), and/or shorts companies expected to experience distress
	Merger arbitrage	Generates returns by going long on the target and shorting the stock of the acquiring company
	Activism	Seeks to obtain representation in companies' board of directors in order to shape company policy and strategic direction
Equity Based	Equity long/short	Consists of a core holding of particular equity securities, hedged with short sales of stocks to minimize overall market exposure
	Equity non-hedge	Commonly known as "stock picking"; invests long in particular equity securities
Macro	Global Macro	Leveraged bets on anticipated price movements of stock markets, interest rates, foreign exchange, and physical commodities
	Emerging markets	Invests a major share of portfolio in securities of companies or the sovereign debt of developing or "emerging" countries; investments are primarily long

Source: (Stowell, 2017)

In some markets, hedge funds are less regulated by the government and are under no obligation to release financial statements or data to the public. This makes measuring hedge fund performance difficult when compared to mutual funds. However, in South Africa, hedge funds are regulated by the Collective Investment Schemes Control Act 2002, this act centres on transparency and investor protection. Under this act, regular reporting to the registrar is a requirement. Studies examining the performance of hedge funds have yielded different results; this lack of harmony, according to Eling and Faust (2010), can be attributed to the different performance methods utilized.

2.4.2 Hedge Fund Performance

Goetzmann, Ibbotson, and Brown (1999) assessed offshore hedge funds over six years and found no persistence of performance; however, they did note that due to the number of dynamic strategies available in the industry, there may be a lack of skill. Goetzmann, Ibbotson, and Brown (1999) only examined offshore hedge funds using annual returns over a relatively short period of time. In contrast this study examines hedge funds in South Africa using monthly data over a longer time period. Boasson and Boasson (2011) examined the performance of hedge funds investment strategies and found that all twelve hedge fund strategies assessed outperformed the market index based on the Carhart (1997) model. Hedge funds employ a number of dynamic strategies and the Carhart (1997) did not adequately capture the different styles used by hedge funds (see; Fung and Hsieh, 2001; Fung and Hsieh, 2004; Agarwal and Naik, 2004) Lawson and Schwartz (2018) observed that when using multifactor models, the generation of alpha was persistent over some time.

Amin and Kat (2003) found that as stand-alone investments, hedge funds did not produce superior risk-adjusted returns. Amin and Kat (2003) used a modified version of the payoff distribution pricing model by Dybvig (1988) and only considered funds with 10 years of consecutive data from 1990. The first South African hedge fund was founded in 1995, the sampling criteria utilised in Amin and Kat (2003) would exclude any South African fund. This study considered funds in the South African context and accounts for survivorship bias by considering both existing and non-existing funds. In Agarwal and Naik (2000) persistence was found when looking at the quarterly return of the hedge funds in question; this persistence reduced as the time period increased, it was also found that very few managers consistently perform over long periods. Agarwal and Naik (2000) assessed the persistence of hedge funds only over short and long periods. The study did not consider persistence in the performance of mutual funds relative to hedge funds as well as emerging markets.

Sun et al. (2014) observed that funds performed better after periods of reduced economic activity; funds were found to persistently perform following periods of hedge fund market weakness or poor economic conditions. The authors constructed two performance measures based on the downside returns and upside returns, funds with higher downside returns were found to consistently perform better. The study focused on how persistent performance during poor market conditions was indicative of fund manager skill. Hsu et al. (2013) also found persistence in the performance of some hedge funds following a crisis. The study evaluated the funds of hedge funds and found that some funds of hedge funds generated significant alphas following a crisis and after an economic downturn or unfavourable economic conditions. This was further observed by Racicot and Theorèt (2013) that hedge fund alphas were high and persistent following a slowdown in economic activity or a downturn in the business cycle, however as economic conditions improved, the reduced alpha was found to be cyclical. Sun, Wang, and Zheng (2018) also found the persistence of hedge fund performance following a downturn in business cycles. The focus of this study however is on the volatility of returns and how that impacts fund performance.

In a study by Fung and Hsieh (1997), four hundred hedge funds and three thousand three hundred and twenty-seven mutual funds were assessed; it was found that hedge funds outperformed mutual funds. Ackermann et al. (2002) realised that hedge funds do not outperform market indices, but they do outperform mutual funds. The performance of hedge funds can be attributed to several characteristics such as complicated and flexible investment strategies, incentive-based compensation systems, limited government regulation and intervention, and sophisticated investors. Liang (1999) found that hedge funds had higher Sharpe ratios and higher abnormal returns when compared to mutual funds. The Sharpe ratio is appropriate when examining the returns of funds that are normally distributed, hedge funds however exhibit non-normal returns. It is not appropriate to use the Sharpe ratio as a measure of performance when the returns do not follow a normal distribution (Eling, 2008).

Capooci (2001) conducted a study consisting of 2796 hedge funds, examining the performance of hedge funds using a combined multifactor capital asset pricing models with an added factor. The study combined the Carhart (1997) the Fama and French (1998) and the models used in Agarwal and Naik (2000). The model consisted of 11 factors including size, value and momentum, a default factor, a factor for funds that invest in non-US equities, and three additional factors that account for hedge funds that invest in the US and foreign bond indices. The model also included a commodity factor and a new factor for funds that invest in emerging market bonds. It was found that the persistence of performance does exist; however, this performance was not constant over the 16 years.

Edwards and Cagayan (2001) studied hedge fund returns over eight years using a six-factor Jensen Alpha to assess performance and hedge fund skill, performance, or alpha. Performance persistence was found; this persistence was present in both the winners and losers in the industry over the period. Furthermore, it was also found that hedge funds with higher incentive structures generated higher excess returns relative to funds with lower incentive structures. This implies a higher payoff for skills and excess return generation; the higher incentive funds were also risker.

Literature on the performance of hedge funds yield different results. Eling and Faust (2010) suggested that this could be as a result of the numerous performance measures used. The performance measure of hedge funds has evolved over time. Hedge funds had a variety of styles and trading strategies, using a performance measure that does not assess the different characteristics was not appropriate Amin and Kat (2003).

Hedge Fund Performance in South Africa: The South African hedge fund industry is still relatively young and small when compared to its global counterparts, as such research in this area is very limited. Botha (2007) assessed the risk measures of hedge funds in the South African context. It was found that the Omega Ratio ranked hedge fund performance better than the Sharpe and Sortino ratios[6]. The study focused on how performance measures ranked the performance of hedge funds .On the contrary this study looks at the performance on funds with the use of factor models, whilst making use of the different performance measures such as the Sharpe, Sortino and Omega ratios. Adenigba (2017) found that hedge funds outperform the South African All Bond Composite Index but do not outperform the JSE All Share Index. The authors also found that hedge funds do not possess' skills concerning market timing ability. The study examines the performance of hedge funds over a ten period using the single factor CAPM, Fama and French (1993), the Carhart (1997) and a market timing model. The authors used CAPM and extension of CAPM to address the performance of hedge funds in the South African context. Due to the complexity of hedge fund strategies, the CAPM model did not sufficiently explain hedge fund returns accurately Fung and Hsieh (2001). The author also examined the relative performance of hedge funds against the JSE All Share Index and the All Bond Composite Index. The study does not consider hedge fund indices or the performance relative to mutual funds.

2.4.3 Hedge Funds: Volatility and Returns

Schneeweis (1998a) examined the performance of hedge funds from 1990 to 1997, and the authors concluded that predictability of future performance of hedge funds was more reliable when volatility was considered as opposed to only finding the historical returns. Agarwal, Arisoy, and Naik (2017) examined the performance of hedge funds and whether the volatility in expected returns attributed to the portfolio returns. Uncertainty or volatility was measured with a VOV measure, which is the volatility of aggregate volatility. In the study, it was found that the portfolios with more negative volatility outperformed their higher volatility counterparts.

[6] Omega Ratio - probability weighted ratio of gains versus losses of a return target. Sharpe Ratio- excess returns above the risk-free rate per unit of risk (standard deviation). Sortino Ratio – excess portfolio returns above a target per unit of downside risk.

Blitz (2018) addressed the volatility anomaly and returns of hedge funds; it was found that although the volatility anomaly was a significant factor in predicting fund returns, aggregate hedge funds tend to favour higher volatility portfolios as opposed to lower volatility portfolios. In the study, the volatility anomaly was captured by the difference between low volatility and high volatility stocks (LV-HV). This factor was then added to the standard Fama-French model. The factor sensitivity that captures the (LV-HV) was found to be negative and statistically significant.

Momoza (2017) assessed the returns of hedge funds in the South African context. The augmented CAPM approach was utilized, and the paper further evaluated the relationship between hedge fund returns and market volatility. In the study, the volatility is represented by the South African Volatility Index (Savi), market volatility does not account for asset or portfolio specific volatility, and a negative correlation was found between the volatility represented by the index and the returns of hedge funds. The study found that the volatility of the index returns had limited explanatory power when it was applied to the hedge fund strategies in South Africa. Momoza (2017) did not explore the relationship between low volatility anomaly and performance measurement in the mutual fund and hedge fund industries. Further, the study relies on the market-wide South African volatility index rather than fund-level volatility to understand the role of fund managers' portfolio choice decisions on fund performance.

2.5 Literature Review Summary

CAPM and multifactor models have been utilized in the assessment of the performance of fund managers and their skills throughout literature. Throughout history, multi-factor models have been developed to improve the explanatory power of variables. Low explanatory power can result in an error in measuring the skill of fund managers or alpha. Empirical studies have identified the presence of a volatility anomaly and how the volatility of returns is an essential factor in determining returns of portfolios or stocks.

Actively managed mutual funds and hedge funds aim to produce absolute positive returns; both attract higher costs relative to funds that follow passive strategies, with higher-performing funds attracting higher costs than passive funds. Performance in both hedge funds and mutual funds has been linked to their abilities concerning market timing, stock selection, and volatility timing. The addition of the volatility anomaly factor to multifactor models or the indirect presence of the volatility anomaly in recently developed or improved multi-factor models have been seen to improve the explanatory power of models. The higher explanatory power of models reduces the presence of alpha.

The literature on the volatility factor and its effects on performance measures such as CAPM and multifactor models are under-explored, especially in developing countries. Most studies have been centred on the presence of the volatility anomaly as opposed to how this presence impacts fund manager performance measures. Failing to account for the volatility anomaly and how this anomaly impacts returns can lead to a gross error in the performance measurement of fund managers.

In South Africa, there have been a few studies done concerning the presence of the volatility anomaly in financial markets; however, there are no studies on how this presence, if accounted for, impact performance measures of mutual fund and hedge fund managers' skills. This study aims to bridge this gap in the literature by assessing the effects of the volatility of returns on predicting returns and how this affects performance measurement of mutual funds and hedge funds in the South African context.

Chapter III: Methodology

This chapter presents the research methodology utilized in the pursuit of a solution for the research problem and objectives. This section will illustrate the methodological steps used to gather data for the study. It will include relevant techniques utilized and how the research will be conducted. This study aims to determine if the volatility of returns is priced in the returns of hedge funds and mutual funds in South African using multifactor capital asset pricing models. The study also aims to determine the effect of the volatility factor and how this impact returns and performance in the hedge fund and mutual fund industries using Jensen's Alpha performance measure.

3.1 Part 1 - Volatility and the South African Context

The returns of mutual and hedge funds are sorted in portfolios based on the volatility of past returns. This is done to determine if the volatility of returns is present in the returns of mutual funds and hedge funds in South Africa and if low volatility portfolios do indeed outperform high-volatility portfolios.

3.2 Part 2- Volatility and Performance

The Carhart (1997) and Fung and Heish (2001) model is used against the portfolios constructed in the study (see section 3.3.3). Performance or alpha is then measured using the Carhart (1997) model for mutual funds and the Fung and Heish (2001) for hedge funds. The two models are combined with Jensen's Alpha (1962) to measure performance in the respective industries. The volatility factor is introduced to the Carhart (1997), and Fung and Heish models, and the regression is rerun. This was done to determine if the introduction of the factor impacts returns and the performance of hedge funds and mutual funds in South Africa.

3.3 Research Models

3.3.1 CAPM and Multifactor Models

The capital asset pricing model (CAPM) and multifactor models are used to theoretically determine the required rate of return of an asset or portfolio. Relative to single-factor models, multifactor models have been empirically proven to have increased explanatory power and flexibility. The arbitrage pricing theory model (APT) is a multifactor model similar to the CAPM. The APT model makes three assumptions; the factor model thoroughly explains returns; there is no arbitrage amongst well-diversified portfolios and diversification eliminates the asset-specific risk (Ross, 2013).

The capital asset pricing model and three multifactor model definitions are illustrated by equations 1, 2, and 3.

$$E(r_i) - rf \ = \alpha + \beta[r_M - r_f] + \varepsilon_t \quad (1)$$

$$E(r_i) = \alpha + \beta_{BTREND}[BTREND] + \beta_{CTREND}[CTREND] + \beta_{FTREND}[FTREND] + \beta_{EQUITY}[EQUITY] + \beta_{ESPREAD}[ESPREAD] + \beta_{BOND}[BOND] + \beta_{BSPREAD}[BSPREAD] + \varepsilon_t \quad (2)$$

$$E(r_i) - rf = \alpha + \beta[r_M - r_f] + \beta_{smb}[SMB_t] + \beta_{hml}[HML_t] + \beta_{mom}[MOM_t] + \varepsilon_t \quad (3)$$

where $E(r_i) - r_f$ represents the excess returns above the risk-free rate. The intercept is α. The systematic risk factor sensitivity of the portfolio is represented by β. The error term is represented by ε_t. The $r_M - r_f$ represents the equity risk premium. The size premium factor sensitivity is β_{smb}. The value premium factor sensitivity is β_{hml}. The momentum factor sensitivity is β_{mom}. The $\beta_{BTREND}, \beta_{CTREND}$ and β_{FTREND} represent the factor sensitivities for bond trends, commodity trends, and currency trends, respectively. The $\beta_{EQUITY}, \beta_{ESPREAD}, \beta_{BOND}$ and $\beta_{BSPREAD}$ are the factor sensitivities for the equity market, the spread in the equity market, the bond market, and the spread in credit spread in the bond market, respectively.

$$E(r_i) - r_f = \alpha + \beta[r_M - r_f] + \beta_{smb}[SMB_t] + \beta_{hml}[HML_t] + \beta_{mom}[MOM_t] + \beta_{vol}[LVH_t] + \varepsilon_t \quad (4)$$

$$E(r_i) = \alpha + \beta_{BTREND}[BTREND] + \beta_{CTREND}[CTREND] + \beta_{FTREND}[FTREND] + \beta_{EQUITY}[EQUITY] + \beta_{ESPREAD}[ESPREAD] + \beta_{BOND}[BOND] + \beta_{BSPREAD}[BSPREAD] + \beta_{LSAVI}[LSAVI] + \varepsilon_t \quad (5)$$

The addition of the volatility factor is illustrated in equations 4 and 5. Equation 4 represents the Carhart (1997) model with the addition of the volatility factor. Equation 5 represents the Fung and Heish (2001) with the addition of the volatility factor. The β_{vol} represents the factor sensitivity for the volatility factor for mutual funds. The β_{LSAVI} represents the sensitivity factor for the volatility factor for the hedge funds.

3.3.2 Performance Measurement: Jensen's Alpha

Jensen's Alpha measures the abnormal returns earned by a particular stock or portfolio compared to the returns suggested by the single factor CAPM model where $r_A - r_M$ is the difference between the realized return of the portfolio and its market proxy, also known as alpha α. This performance measure is also the intercept of the regression illustrated in equation 6. If the alpha represented by this regression is positive and also statistically significant, then the portfolio has outperformed its market proxy. A positive alpha illustrates that the manager has added value.

The measurement of alpha can be expanded to all the multifactor model definitions, which is illustrated in equations 7, 8, 9, 10, and 11 creating a multi-factor benchmark.

$$r_A - r_m = \alpha \tag{6}$$

$$r_A - r_f = \alpha + \beta_A[r_M - r_f] + \varepsilon_t \tag{7}$$

$$r_A = \alpha + \beta_{BTREND}[BTREND] + \beta_{CTREND}[CTREND] + \beta_{FTREND}[FTREND] + \beta_{EQUITY}[EQUITY] + \beta_{ESPREAD}[ESPREAD] + \beta_{BOND}[BOND] + \beta_{BSPREAD}[BSPREAD] + \varepsilon_t \tag{8}$$

$$r_A = \alpha + \beta_{BTREND}[BTREND] + \beta_{CTREND}[CTREND] + \beta_{FTREND}[FTREND] + \beta_{EQUITY}[EQUITY] + \beta_{ESPREAD}[ESPREAD] + \beta_{BOND}[BOND] + \beta_{BSPREAD}[BSPREAD] + \beta_{LSAVI}[LSAVI] + \varepsilon_t \tag{9}$$

$$r_A - r_f = \alpha + \beta_A[r_M - r_f] + \beta_{smb}[SMB_t] + \beta_{hml}[HML_t] + \beta_{mom}[MOM_t] + \varepsilon_t \tag{10}$$

$$r_A - r_f = \alpha + \beta_A[r_M - r_f] + \beta_{smb}[SMB_t] + \beta_{hml}[HML_t] + \beta_{mom}[MOM_t] + \beta_{vol}[LVH_t] + \varepsilon_t \tag{11}$$

where $r_A - r_m$ represents the difference between the return on the portfolio and the return on its market proxy portfolio, the excess return with regard to the risk-free rate is represented by $r_A - r_f$. The alpha constant is represented by α. The systematic risk factor sensitivity of the portfolio is represented by β_A.

3.4 Model Factor Calculation and Construction

3.4.1 Mutual Funds - Model

The models applicable to mutual funds illustrated in section 3.3.1 and 3.3.2 are as follows:

$$r_A - r_f = \alpha + \beta_A[r_M - r_f] + \beta_{smb}[SMB_t] + \beta_{hml}[HML_t] + \beta_{mom}[MOM_t] + \varepsilon_t$$

$$r_A - r_f = \alpha + \beta_A[r_M - r_f] + \beta_{smb}[SMB_t] + \beta_{hml}[HML_t] + \beta_{mom}[MOM_t] + \beta_{vol}[LVH_t] + \varepsilon_t$$

Excess Market Return: The excess market return is calculated as the total return less the identified risk-free rate at each period.

Risk-Free Rate: The risk-free rate is taken as the South African 10-year domestic government bond rate at the time "t."

Beta: Beta is calculated as the covariance of returns between the market and the asset, divided by the variance of the market.

$$\beta = \frac{Cov(r_i, r_m)}{Var(r_m)}$$

Small Minus Big – Size: The size premium represents the premium applicable to small-capitalization stocks relative to large-capitalization stocks. The size premium factor is calculated similar to Fama and French (1993), by taking the share price of the firm or fund and multiplying the number of outstanding shares and the share price at the end of June at the time "t."

$$Size = Price\ of\ Equity_t * Number\ of\ shares\ outstanding$$

High minus Low - Book to Market: Book-to-Market is calculated as the market value of equity as at time "t" divided by the book value of equity as at the end of December "t-1" for time "t."

$$Market\ to\ Book_t = \frac{Market\ Value\ of\ Equity_{\ t}}{Book\ Value\ of\ Equity_{t-1}}$$

The funds were sorted from small to substantial based on the value of the market to book ratio, value funds, or stocks have a small market to book ration, and growth funds have a large market to book ratio.

Winners Minus Losers – Momentum: Similar to the Carhart (1997) model, the momentum factor looks at "winners," funds were sorted from worst to best (losers to winners) concerning stock performance, a stock shows momentum if the prior 12-month returns have been positive.

Volatility: Similar to the methodology used in Ang, Hodrick, Xing, and Zhang (2006), the volatility factor was constructed from the payoff of a synthetic one month at the money put and call options on the JSE All Share Index. Option prices reflect volatility, as volatility increases, so do the price on derivative contracts.

3.4.2 Portfolios – Factor construction

Constructing Right-Hand Side Factors: An approach similar to the Fama and French (2015) and Lin (2017) methodology is used to construct the right-hand side factors. In the first approach, factors are constructed based on 2x3 sorts; in the second approach, factors are constructed based on 2x2 sorts, and in the third approach, factors are constructed using 2x2x2 sorts. The size premium factor is calculated as the mean returns on the small-capitalization funds minus the large-capitalization funds. The value premium factor is calculated as the mean return on the funds with high book to market ratios or value stocks minus the mean returns of the funds with a low book-to-market ratio or growth funds. The winners' premium factor is calculated as the mean returns on the winners' funds minus the mean returns on the loser funds.

3.4.2.1 Approach 1 – 2x3 sorts and Factor Construction

Six value-weighted portfolios were created based on the intersection of the size momentum and book-to-market groups. Size is grouped or sorted based on a median point creating two groups, the small (S) and big (B) groups. The other two variables were sorted based on the bottom 30th percentile, 40th percentile, and 30th percentile. For the book-to-market variable, the new groups or portfolios are valued (V) neutral (N) and growth (G). For the momentum variable, the new groups are the winners (W) average (A) and Losers (L).

Table 1 Approach 1

SIZE	$SMB\ (B/M) = \frac{(SV + SN + SG) - (BV + BN + BG)}{3}$ $SMB\ (MOM) = \frac{(SW + SA + SL) - (BW + BA + BL)}{3}$ $SMB = \frac{SMB(B/M) + SMB(MOM)}{2}$
BOOK TO MARKET	$HML = \frac{(SV + BV) - (SG + BG)}{2}$
MOMENTUM	$MOM = \frac{(SW + BW) - (SL + BL)}{2}$

3.4.2.2 Approach 2 - 2x2 sorts and Factor Construction

Size is grouped or sorted based on a median point creating two groups, the small (S) and big (B) groups. The other two variables were sorted based on the median point. For the book-to-market variable, the new groups or portfolios are value (V) and growth (G). For the momentum variable, the new groups are the winners (W) and Losers (L).

Table 2 Approach 2

SIZE	$SMB = \frac{(SV + SG + SB + SW) - (BV + BG + BB + BW)}{4}$
BOOK TO MARKET	$HML = \frac{(SV + BV) - (SG + BG)}{2}$
MOMENTUM	$MOM = \frac{(SW + BW) - (SL + BL)}{2}$

3.4.2.3 Approach 3 – 2x2x2 sorts and Factor Construction

Based on the median breakpoint, 2x2x2 portfolio sorts were created based on the median points of each variable.

Table 3 Approach 3

SIZE	$SMB = \frac{(SVW + SGW + SGL + SVL) - (BVL + BGW + BGL + BVW)}{4}$
BOOK TO MARKET	$HML = \frac{(SVW + SVL + BVL + BVW) - (SGW + SGL + BGW + BGL))}{4}$
MOMENTUM	$MOM = \frac{(SVW + SGW + BGW + BVW) - (SVL + SGL + BVL + BGL)}{4}$

3.5. Hedge Funds

3.5.1 Hedge Fund Models

The models applicable to hedge funds illustrated in section 3.3.1 and 3.3.2 are as follows:

$$r_A = \alpha + \beta_{BTREND}[BTREND] + \beta_{CTREND}[CTREND] + \beta_{FTREND}[FTREND] + \beta_{EQUITY}[EQUITY] + \beta_{ESPREAD}[ESPREAD] + \beta_{BOND}[BOND] + \beta_{BSPREAD}[BSPREAD] + \beta_{LSAVI}[LSAVI] + \varepsilon_t$$

$$r_A = \alpha + \beta_{BTREND}[BTREND] + \beta_{CTREND}[CTREND] + \beta_{FTREND}[FTREND] + \beta_{EQUITY}[EQUITY] + \beta_{ESPREAD}[ESPREAD] + \beta_{BOND}[BOND] + \beta_{BSPREAD}[BSPREAD] + \varepsilon_t$$

Excess Market Return: The excess market return is calculated as the total return less than the identified risk-free rate at each period.

Risk-Free Rate: The risk-free rate is taken as the South African 10-year domestic government bond rate at the time "t."

Trend Following and Volatility Factors : Trend factors and volatility factors were constructed using the payoff of a look back long straddle position. A long straddle position is one where the owner hedges possible risk or uncertainty by taking long (buying) positions in both put and call options. The put (long) options limit downside exposure if the price of the underlying asset drops and call (long) options are beneficial when the price of the underlying is rising. Straddles offer unlimited upside potential while shielding against any downsides. Fung and Heish (2001) implement this strategy in factor construction by creating long positions that are at the money. For a straddle to work, the underlying asset must be the same, and the strike price or exercise price must be the same. Positions are created for both an up and down movement in the market and are combined to form factors.

Equity Factors : Equity factors were calculated based on the fund's exposure to the equity market.

Bond Factors : Bond factors were calculated based on the fund's exposure to the bond market.

3.5.2 Factor construction and calculation.

Similar to the methodology utilized by Fung and Heish (2001). Factors were constructed based on trend following, exposure to equity factors, and exposure to bond factors based on the arbitrage pricing theory. Similar to Agarwal et al. (2017), a volatility factor was added to the model based on the payoff of a look back straddle of the South African Volatility Index (SAVI). An extra element to account for the volatility of returns is added to the model.

Trend Factors: Trend factors were calculated based on the payoff of a long straddle position based on a ten-year look-back period in the derivatives market in the South African Context.

Bond Trend – A lookback straddle on the bond market

Currency Trend – A lookback straddle on the forex market

Commodity Trends – A lookback straddle on the commodity market

Equity Factors : Equity Market Factor – the total monthly return on the JSE All-share Index.

The Size Spread Factor – small-cap JSE index (below ZAR1billion) – a large-cap index (above ZAR10 billion)

Bond Factors : The change in the yield on the 10-year Treasury bond (month-end to month-change) over the time horizon.

The Credit Spread Factor – the change in the yield of the monthly credit spread (spread is calculated as the 10-year corporate bond yield in South Africa less than the 10-year Treasury bond yield adjusted for the duration).

Volatility Factor : Low volatility factor – the payoff of a ten-year lookback straddle on the SAVI index.

3.6 Portfolio Construction

3.6.1 Portfolio Construction- Mutual Funds

Similar to the Jordan and Riley (2015), ten equally weighted portfolios were constructed to evaluate if volatility is priced in the South African context and how the introduction of the low volatility factor impacts the returns of the portfolios.

Market Portfolio Construction – Mutual Funds : The JSE All Share Index was used as a proxy for the expected market return for mutual funds.

3.6.2 Portfolio Construction- Hedge Funds

The hedge fund portfolios were constructed based on equal weights of the most popular strategies found in the South African Context. The portfolios include strategies from the fixed-income arbitrage strategy, multi-strategy, long-short equity strategy, and the market-neutral equity strategy.

Funds of Funds were not included in portfolio construction to avoid double counting.

3.7 Data

3.7.1 Data Collection

The data utilized in the research is primarily secondary. These are data sets that have been collected by someone else for another purpose (Johnston, 2017. The data sourced for the research originated from large data or information providers who are well respected in the relevant industries and are illustrated in table 4.

Table 4 Data Sources

Data Source	Type of Data
Profile Data	Monthly Returns (mutual funds)

Hedge News Africa	Monthly Returns (hedge funds)
The South African Reserve Bank	Risk-Free Rate
Bloomberg	Company Specific Data
Inet	Company Specific Data
Inet, Bloomberg, Hsieh (RFS, 2001)	ALSI, SAVI, Derivative Markets, Trend Factors

3.7.2 Population and Sample

In South Africa, there are 1261-unit trusts, and 1,171 actively managed registered unit trusts. Two hundred ninety-five hedge funds are registered in South Africa. When compared to developed markets, the population of both hedge funds and mutual funds is relatively small.

3.7.3 Sample Selection

The study consisted of two samples, one for hedge funds and one for mutual funds. The sample period considered was from 2007 to 2018. The sample period from 2007 to 2018 aims to capture the two industries in various market conditions and it includes the global financial crisis.

Hedge funds: In South Africa, there are six major hedge fund strategies. Namely, equity long/short, equity neutral, fixed income, statistical arbitrage, volatility arbitrage, and multi-strategy strategies. The study considered hedge fund data from all strategies. Funds of Funds were not included to avoid double counting.

Mutual Funds: ASISA (The Association for Savings and Investment South Africa) classifies funds based on geography, principle, and main investment focus. This study is focused on the South African Equity General Category (293 funds).

3.7.4 Factors considered in Sample Selection

Survivorship bias is an upward bias caused by only considering the performance information of funds that have survived or still exist; Pawley (2006) cautions that survivorship bias can produce misleading results. The study considered all existing and non-existing funds during the sample period to avoid such bias. Any non-existing funds or portfolios that are no longer in existence at the measurement date were included in portfolio construction and return measurement. This study focuses on funds that generate alpha, or claim superior performance relative to the market. Index or passive funds are removed from the sample. Newly established funds with performance data of less than 24 months were removed from the sample.

Chapter IV: Data analysis

This section details the research data analysis component of the study. The data analysis was done on EVIEWS 10 data analysis software. The section will look into the descriptive statistics of the data sets, regression analysis, and interpretation of results. The study aims to assess the impact of the low volatility anomaly on the alpha of hedge funds and mutual funds. This section has two subsections of data analysis; the first section will assess the impact of volatility on hedge funds, and the second section will evaluate the effect of volatility on mutual funds.

4.1. Hedge Funds.

The hedge fund data was collected from Hedge News Africa, and the data were collected based on the different strategies utilized in the South African hedge fund industry. The data are based on the median returns of each strategy. The Hedge Fund Strategies are:

- South Africa Single-Manager Composite (ASMI)
- Long/Short Equity Index (ALSI)
- Market Neutral & Quantitative Index (AMINI)
- Multi-Strategy Index (AMSI)
- Fixed Income Index (AFII)
- Event-Driven / Credit Index (AIDI)

4.1.1 Trend Analysis

Below (figure 7) is a pictogram showing the movement of the variables in the Hedge fund model. It can be observed that the variables were generally volatile in the period under investigation. This excludes the Equity and the Equity Spread, which shows lower levels of fluctuations. A trend analysis is a technique that investors utilize to spot different patterns in the data and also to gather information (Murphy, 1999).

Of all the hedge fund strategies, the Event-Driven / Credit Index (AIDI) strategy, when looking at the pictogram, appears to be the least volatile. The strategy aims to capitalize on inefficiencies that arise from different corporate events in financial markets such as mergers, acquisitions, and companies in financial distress (Srivastava, 2019). Such events are not as unpredictable as movements in the stock market. Of all the factors considered in the model, the Equity and Spread factors had the lowest level of fluctuations or volatility.

Figure 7- Trend Analysis – Hedge Funds

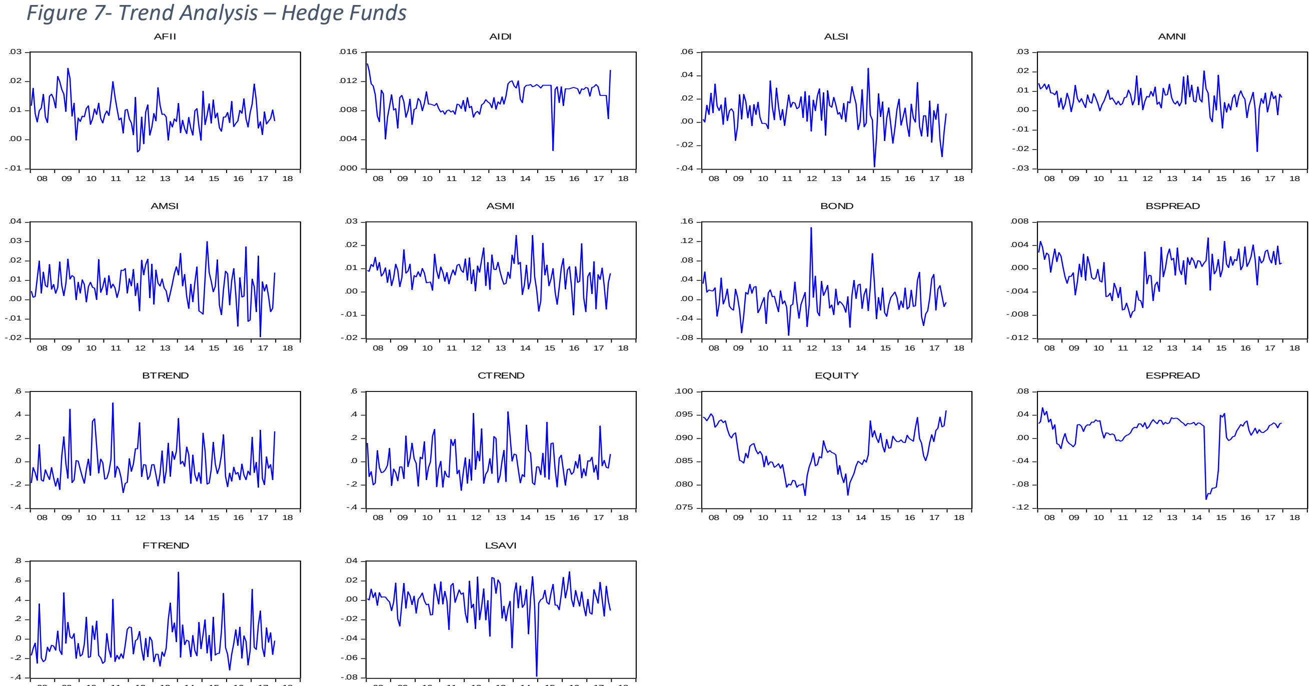


Figure 7 above illustrates a trend analysis on the different hedge fund strategies and the factors utilised in the model in chapter 3. All the variables above are quite volatile with the exception of the equity factor and the e-spread factor. The meanings of acronyms are as follows: South Africa Single-Manager Composite- ASMI; Long/Short Equity Index –ALSI; Market Neutral & Quantitative Index – AMINI; Multi-Strategy Index- AMSI; Fixed Income Index –AFII; Event-Driven / Credit Index –AIDI; Bond Trend Factor – BTREND; Commodity Trend Factor – CTREND; Currency Trend Factor- FTREND; Equity Market Factor – EQUITY; Equity Market Spread – ESPREAD; Bond Market Factor – BOND; Bond Market Spread – BSPREAD; Volatility Factor - LSAVI

The Equity factor looks at the total return on the JSE Index whilst the Equity Spread factor looks at the difference between the small-cap index and the large-cap index in South

Africa. Both factors are relatively less volatile than the other factors, which is surprising when looking at the bond and bond spread factors. Equities have been known to be much more volatile than bonds. Long term bonds, however, have been found to be riskier than equities (Jung, Shambora & Choi, 2010).

4.1.2 Descriptive statistics

This section will analyse the mean, standard deviation, and skewness of the Hedge funds returns. The mean is the average returns of the hedge funds during the period under consideration. The standard deviation illustrates how much the hedge fund returns deviated from the average value over the period under consideration. In addition, the skewness demonstrates how much the returns deviate from a standard normal distribution.

Table 6: Descriptive Statistics – Hedge Funds

Hedge Funds	AFII	AIDI	ALSI	AMNI	AMSI	ASMI
Mean	0.009	0.010	0.008	0.006	0.007	0.007
Standard Deviation	0.005	0.002	0.014	0.005	0.009	0.006
Skewness	0.394	-0.555	-0.292	-0.809	-0.182	-0.192
Sharpe ratio	0.673	2.341	0.208	0.134	0.234	0.335
Kurtosis	3.588	4.269	3.643	7.627	3.374	3.890
P-value of Jarque-Bera	0.089	0.001	0.151	0.000	0.505	0.096
Omega ratio	6.620	99.697	1.682	1.464	1.805	2.334

Table 6 above illustrates the descriptive statistics for the period under investigation. The Unit Trust portfolios specifically under the equity general category were placed into ten portfolios annually over the ten year period with portfolio one representing the portfolio with the lowest variability in returns and portfolio ten representing the portfolio with the highest variability.The meanings of acronyms are as follows: South Africa Single-Manager Composite- ASMI; Long/Short Equity Index –ALSI; Market Neutral & Quantitative Index –AMINI; Multi-Strategy Index- AMSI; Fixed Income Index –AFII; Event-Driven / Credit Index –AIDI; Bond Trend Factor – BTREND; Commodity Trend Factor – CTREND; Currency Trend Factor- FTREND; Equity Market Factor – EQUITY; Equity Market Spread – ESPREAD; Bond Market Factor – BOND; Bond Market Spread – BSPREAD; Volatility Factor - LSAVI

The South African Event-Driven index (AIDI) had an average return of 0.96%, which is the highest average return among the hedge funds under consideration. The South African Market Neutral Index recorded the lowest average return of 0.6%. The South African Multi-strategy index (AMSI) reported a standard deviation of 0.19%. Also of note is the South Africa Long Short Index (ALSI), which recorded a standard deviation of 1.4%.

The equity long-short hedge fund strategy reported the highest standard deviation. The strategy aims to reduce market exposure by taking long positions in undervalued securities and short positions in overvalued securities, this kind of strategy is perilous as it involves taking different speculative positions in the market; the strategies utilized also includes a significant amount of leverage which increases risk whilst also increasing potential returns, and short-selling can also involve a significant amount of downside risk (May, 2004).

The lowest standard deviation in absolute terms was recorded by the South African Event-Driven Index (AIDI), which recorded a standard deviation of 0.19%. Event-driven investing aims to take advantage of inefficiencies in the market around different corporate and company-specific events and has been found to historically perform well (Srivastava, 2019). Event-driven strategies also have a low correlation with the market, strategies looking at events such as mergers work well in economic booms, strategies looking at events that deal with financial distress work well in times of economic hardship (Teun, 2007).

When looking at performance relative to volatility, the fund with the lowest standard deviation reported the highest return. This finding is not surprising, as Haugen and Heins (1972), Haugen and Baker (1991) and Baker and Haugen (2012) illustrate that portfolios with higher volatility have a tendency to underperform their lower volatility counterparts. When looking at the time period under investigation, the South African Event-Driven Index (AIDI), which reported the highest average return and lowest volatility of returns, outperformed its higher volatility counterparts.

Risk-return measures are important in the investment industry. They assist investment professionals in assessing the attractiveness of hedge funds (Rambo & Van Vuuren, 2017). The Sharpe[7] and the Omega[8] ratios examine the hedge fund performance in South Africa over the period under examination and are illustrated in Table 6. All the computed Sharpe ratios are positive. The Event-driven/Credit Index (AIDI) had the highest Sharpe and Omega ratios relative to the other strategies. The Sharpe ratio, however, is not appropriate as a performance measure for funds that exhibit non-normality. When there are deviations from normality, the use of the Sharpe ratio is not adequate as a performance measure (Eling, 2008).

Botha (2007) found that in South Africa when looking at the risk measures of hedge funds, found that the Omega ratio ranked hedge fund performance much better than the Sharpe and Sortino Ratios. Both the Sharpe and Omega ratios in the results presented above ranked the hedge fund performance identically. The Omega ratio takes into account the skewness and kurtosis. Botha (2007) and identifies portfolios or funds that generate more positive excess returns relative to losses. The AIDI strategy has the highest Omega ratio suggesting a higher probability of gains over the period.

Investors look up to skewness to check the downside or the upside risk of their investments. Returns that have negative skewness are preferred because they have less downside risk, while returns that have positive skewness are not preferred because more observations lie on the negative territory, thus suggesting a great downside risk. Using this basis to judge the Hedge funds, we can see that the South African Market neutral Index (AMINI) is preferable because of its skewness coefficient of -0.8097.

The kurtosis statistic for all the hedge fund returns is greater than three, suggesting that the data set has fatter tails relative to a normal distribution. Hedge fund strategies have been found to exhibit negative skewness and excess kurtosis relative to a normal distribution (Lamm, 2003). When looking at the Jarque-Bera statistic, at the 5% level of significance, the assumption of normality can be rejected for the return distributions of

[7] The Sharpe ratio looks at the excess returns per unit of risk
[8] The Omega ratio evaluates a portfolios gains above or losses below a certain return threshold

AIDI and AMNI only, which is surprising because hedge funds have been known to have non-normal option-like returns (Gregoriou, Sedzro & Zhu, 2005).

Furthermore, Amin and Kat (2003) do not find persistent performance in hedge funds when looking at their risk-adjusted returns. This is in line with the negative Sharpe ratio, the numerator of the Sharpe ratio (excess returns) is negative, suggesting that after considering the risk free rate, hedge funds do not produce positive returns.

4.1.3 Correlations

Correlations measure the relationship between one or more variables (Kenny,1979). The correlation analysis is utilized in finance and asset management for diversification purposes. In this section, the correlations of Hedge funds returns are under consideration. For more correlations, see the appendix.

A strong positive correlation (0.71506**)** can be observed between ALSI and AMSI. This means that the returns for the Long Short Index and the Multi-strategy Index move together over time. Using negatively correlated assets as a guideline to diversification, a combination of ALSI and AMSI in the same portfolio would not be plausible. A Strong positive correlation can be observed between ALSI and ASMI (0.89661). This correlation coefficient suggests that returns of these indexes mirror each other over time.

Table 7: Correlation matrix

	AFII	AIDI	ALSI	AMINI	AMSI	ASMI
AFII	1					
AIDI	-0.14586	1				
ALSI	-0.01056	-0.18883	1			
AMINI	-0.04847	-0.02732	0.56383	1		
AMSI	0.13024	-0.15980	0.71506	0.40592	1	
ASMI	0.12444	-0.10832	0.89661	0.6754	0.8340	1

AFII and AIDI returns have a weak negative correlation (-0.14586) illustrating that the returns have an inverse relationship: when one index increases, the other falls, on average, across time. Such negative correlations form the basis for diversification. Another negatively correlated pair is ALSI and AIDI (-0.18883). This also shows that the returns of the Long Short Index and the Event Driven Index have a negative relationship.

4.1.4 Regression Analysis – No Volatility Factor

This section details the econometric analysis of the data using the specified models explained in chapter 3.

As shown in Table 8, the results illustrate that the constant (alpha) of the hedge fund strategies are all insignificant at the 5% level of significance, with the exception of the (AFII) and (AIDI). The performance of hedge funds can be attributable to a number of factors such as incentive-based compensation, flexibility to execute different strategies, and the ability to use leverage. Some authors attribute the performance of hedge funds to the cyclicality of financial markets: hedge fund performance has been found to be weakly or negatively correlated to the asset classes such as equities or bonds and have been found to significantly outperform after an economic downtown (see, Hsu et al., 2013; Racicot & Theorèt, 2013, Sun et al., 2014; and Sun et al., 2018).

Table 8: Regression results-Hedge fund analysis, no volatility factor

.Dependent Variable	**AFII**	**AIDI**	**ALSI**	**AMNI**	**AMSI**	**ASMI**
CONSTANT	-0.0385*** (0.003)	0.0095*** (0.002)	0.0611 (0.061)	0.0270 (0.019)	0.0171 (0.044)	0.0211 (0.038)
BTREND	-0.0009 (0.001)	-0.0009*** (0.000)	-0.0381*** (0.013)	-0.0062*** (0.000)	-0.0173 (0.021)	-0.0146** (0.007)
CTREND	-0.0004 (0.001)	-0.0007 (0.001)	0.0118*** (0.004)	0.0012 (0.003)	0.0053 (0.011)	0.0039 (0.003)
FTREND	0.0030*** (0.001)	0.0020*** (0.000)	0.0020 (0.008)	-0.0042* (0.002)	0.0046 (0.017)	0.0012 (0.002)

EQUITY	0.5426*** (0.033)	0.0038 (0.016)	-0.6303 (0.717)	-0.2456 (0.220)	-0.1191 (0.537)	-0.1667 (0.434)
ESPREAD	-0.0075 (0.017)	-0.0061 (0.004)	0.0781** (0.038)	0.0162 (0.014)	0.0181 (0.011)	0.0313** (0.013)
BOND	-0.0732*** (0.008)	0.0011 (0.003)	-0.0192 (0.076)	0.0234** (0.011)	-0.0272 (0.114)	-0.0100 (0.031)
BSPREAD	-0.5787*** (0.102)	0.1728*** (0.021)	-0.3600 (0.913)	0.2936 (0.246)	-0.3900** (0.171)	-0.1842 (0.556)
Adj R-square	0.282	0.083	0.214	0.073	0.065	0.118
Durbin Watson	1.568	1.387	2.130	1.622	2.073	1.915
Prob (F-stat)	0.000	0.018	0.000	0.029	0.041	0.003

*This table illustrates the merged regression results for the benchmark model without the volatility factor, in brackets are the standard errors. The table also illustrates the adjusted R- squared, the Durbin Watson statistic, which tests for autocorrelation in the model and the F- Statistic, which illustrates the goodness of fit of the model. The problem of autocorrelation, if present in any model, was solved using the Newey- West specification, which allows for the standardization of the error terms. *, ** and *** respectively shows that the reported coefficients are statistically significant at 1%, 5%, and 10% confidence levels; South Africa Single-Manager Composite- ASMI; Long/Short Equity Index – ALSI; Market Neutral & Quantitative Index –AMINI; Multi-Strategy Index- AMSI; Fixed Income Index –AFII; Event-Driven / Credit Index –AIDI; Bond Trend Factor – BTREND; Commodity Trend Factor – CTREND; Currency Trend Factor- FTREND; Equity Market Factor – EQUITY; Equity Market Spread –SPREAD; Bond Market Factor – BOND; Bond Market Spread - BSPREAD*

Hedge funds also utilize a number of strategies and have different incentive structures relative to mutual funds. Funds that offer grand incentive schemes have also been found to generate higher excess returns (Edwards & Caglayan, 2001), this implies a higher payoff for hedge fund managers in return for the generation of excess returns. Furthermore, Edwards and Caglayan (2001) also observed that funds with higher incentive structures had a higher excess return. Contrary to this, some authors have not found persistent performance when looking at hedge funds. Amin and Kat (2003) and Goetzmann et al. (1999) have found that hedge funds do not produce superior returns.

The bond trend factor (BTREND) and credit spread factor (BSPREAD), as illustrated in Table 8, is significant in a number of hedge fund strategies examined. This finding is not surprising. Eling and Faust (2010) argued that emerging markets are faced with substantial credit risk when investing in both corporate and government bonds in their relevant locations, and as such, credit spread is an essential factor to hedge funds in emerging markets. The currency trend (FTREND), as illustrated above, is significant in three out of the six strategies examined. Hedge fund managers can invest in different currencies or strategies other than the base currency exposing funds to exchange rate risk. Hedge funds can use various strategies and derivative instruments such as futures or forwards to take speculative, hedging or arbitrage positions in financial, commodity, or forex markets. Hedge fund returns are related to the different markets in which they take positions (Lambert, 2012).

When looking at the model validity, the F-Statistic is considered. The F-stat is significant at 5% for all the strategies considered. The Adjusted R squared, however, is low for all the models. The highest adjusted R squared was 28.2%, which belongs to Africa Fixed Income Index (AFII). The low R-Squared, however, is inconsistent with literature, Cephas (2013) model adapted from Fung and Heish (2004) explained 75% variability in hedge fund returns in South Africa. Cephas (2013) utilized a 9-factor model that combined the Carhart (1997) model and the Fung and Heish (2004), the market factor was excluded from the model. Fama and French (1992) found that R^2 usually is low in cross-sectional data and higher in time series.

Thus, Achen (1982) rejected the use of the coefficient of determination as it only explains variances in regression. A combination of time series data and cross-sectional data will increase R^2 if at least a dummy variable is included in the estimated regression model. Furthermore, Mayer (1975) argued that in the event that R^2 is low, the goodness of fit of the model would be based on F-static and F-probability values. The contradiction in results could also be attributable to model differences or company-specific factors.

4.1.5 Regression Analysis – With the Volatility Factor

In this section, the Volatility Factor is added to the previous models to find out its impact on the hedge funds alpha. The results are presented in Table 4.4. At the 5% level of significance, the AMNI, AMSI, and ASMI model constants (alpha) in the volatility augmented models for the hedge funds became significant in the models. The ALSI volatility augmented model became significant at the 1% level. In the volatility-augmented model for AFII and AIDI, the constant remained significant, however, at the 1% and 5% levels, respectively. There was a marginal fall in some of the strategies examined; in the

AFII model, the constant remained unchanged. The addition of the volatility increased the constant in the ALSI model.

By adding the volatility factor, the model constants became significant in four of the six strategies examined (ALSI, AMNI AMSI, and ASMI) and remained significant in two of the six strategies examined (AFII and AIDI). Although there was a marginal fall in the constant of some of the funds, which is expected, the findings in table 9 are inconsistent with the literature: Jordan and Riley (2015) found that inclusion of the volatility factor reduced the presence of alpha and, in some cases, resulted in an insignificant or zero alpha. The constants in Table 9 were also positive this finding is surprising, Kaeck (2018) illustrated that the inclusion of the variance-of-variance (volatility) factor after adjusting for Fama-French and Carhart risk factors resulted in a negative constant.

Table 9 : Regression results-Hedge fund analysis, with the volatility factor						
Dependent Variable	AFII	AIDI	ALSI	AMNI	AMSI	ASMI
CONSTANT	-0.0382*** (0.0111)	0.0090** (0.0045)	0.0874*** (0.0290)	0.0332** (0.0131)	0.0349** (0.0198)	0.0337** (0.0140)
BTREND	-0.0010 (0.0034)	-0.0010 (0.0014)	-0.0275*** (0.0088)	-0.0036 (0.0040)	-0.0100 (0.0060)	-0.0096* (0.0042)
CTREND	-0.0004 (0.0030)	-0.0007 (0.0012)	0.0100 (0.0071)	0.0008 (0.0035)	0.0042 (0.0053)	0.0030 (0.0037)
FTREND	0.0030 (0.0027)	0.0020** (0.0011)	0.0022 (0.0071)	-0.0042 (0.0032)	0.0048 (0.0048)	0.0013 (0.0034)
EQUITY	0.5391*** (0.1265)	0.0084 (0.0513)	-0.9198*** (0.3302)	-0.3139** (0.1450)	-0.3161 (0.2250)	-0.3053 (0.1590)
ESPREAD	-0.0079 (0.0152)	-0.0055 (0.062)	0.0414 (0.0398)	0.0076 (0.0181)	-0.0067 (0.0271)	0.0137 (0.0192)
BOND	-0.0726*** (0.0143)	0.0004 (0.0058)	0.0249 (0.0375)	0.0338 (0.0170)	0.0029** (0.0255)	0.011314 (0.0181)
BSPREAD	-0.5740*** (0.1738)	0.1666** (0.0062)	0.0319 (0.4539)	0.3859 (0.2059)	-0.1232* (0.3092)	0.0035 (0.2186)
LSAVI	0.0037 (0.0037)	-0.0049 (0.0124)	0.3118*** (0.0796)	0.0735 (0.0361)	0.2122* (0.0542)	0.1493** (0.0383)
Adj R-square	0.2758	0.076505	0.3032	0.0980	0.1710	0.2175
Durbin Watson	1.5699	1.3799	2.0432	1.5911	2.0121	1.8608

Prob (F-stat)	0.000	0.03013	0.0000	0.0116	0.0003	0.0000

*Table (9) .This table illustrates the merged regression results for the benchmark model with the volatility factor, in brackets are the standard errors. The table also illustrates the adjusted R- Squared, the Durbin Watson statistic which tests for auto correlation in the model and the F- Statistic which illustrates the goodness of fit of the model. The problem of autocorrelation if present in any model was solved using the Newey- West specification which allows for the standardization of the error terms. *, ** and *** respectively shows that the reported coefficients are statistically significant at 1%, 5% and 10% confidence levels; South Africa Single-Manager Composite- ASMI; Long/Short Equity Index –ALSI; Market Neutral & Quantitative Index –AMINI; Multi-Strategy Index- AMSI; Fixed Income Index –AFII; Event-Driven / Credit Index –AIDI; Bond Trend Factor – BTREND; Commodity Trend Factor – CTREND; Currency Trend Factor- FTREND; Equity Market Factor – EQUITY; Equity Market Spread – ESPREAD; Bond Market Factor – BOND; Bond Market Spread - BSPREAD*

The presence or persistence of the constant in this study could be explained by fund specific characteristics not captured in the model or other factors that are not included in the model. In the table above, the volatility factor (LSAVI) was significant in three out of the six hedge fund portfolios. The significance of the volatility factor is in agreement with literature: risk is an important input across all financial markets. Agarwal et al. (2017) found the volatility factor to be significant.

The volatility factor (LSAVI) is positive and significant in three of the six strategies examined, and this finding is surprising. The volatility factor in literature has been found to be negative and significant (see, Agarwal et al., 2017). Blitz (2018) also found that the volatility factor for hedge fund returns was negative, suggesting that an increase in volatility leads to a decrease in hedge fund returns holding all other variables constant. Dash and Moran (2005) looked at the Chicago Board Options Exchange (CBOE) Volatility Index (VIX) and its correlation to hedge funds. VIX was found to be negatively correlated to hedge fund returns, which is line with the findings by Momoza (2017), who conducted a study in South Africa looking at the relationship between hedge fund returns and the South African Volatility Index (SAVI). A negative relationship was found, but SAVI had limited explanatory power. The positive volatility factor found in this study suggests that hedge funds “bet” on volatility as opposed to betting against it. The study suggests that an increase in the volatility factor increases hedge fund returns in some of the hedge fund portfolios.

The addition of the volatility factor improved the adjusted r-squared model slightly in some of the models but remained low. Furthermore, the model with the highest explanatory power reported and adjusted R-Squared of 27.58%. The low explanatory power of the volatility augmented model could be due to variables not included in the model. Introducing the volatility factor did not significantly improve the explanatory power of the volatility augmented model compared to the model without volatility. On the contrary, the inclusion of the volatility factor in Jordan and Riley (2015) led to an improvement in the explanatory power of the model. Furthermore, Kuenzi and Shi (2007) compared different volatility factors and their explanatory power when looking at hedge fund returns. The volatility factor constructed from puts and calls on market indices had a high and significant explanatory power. In this study, the explanatory power of the volatility augmented models is very low across all the strategies.

4.2 Unit Trusts (Mutual Funds)

This section details the analysis of unit trust (mutual fund) return models. The portfolios 1-10 are sorted according to their volatility from the less volatile to the most volatile over the time period. As explained in Chapter 3, factors are computed based on 2*2, 2*3, and 2*2*2 portfolio sorts. Factors calculated from emerging markets are also utilized in this section. The unit trust portfolios were modelled first, excluding the volatility factor, then secondly, including the volatility factor based on the equations in chapter 3.

Figure 8 - Trend analysis – Unit trust Portfolios

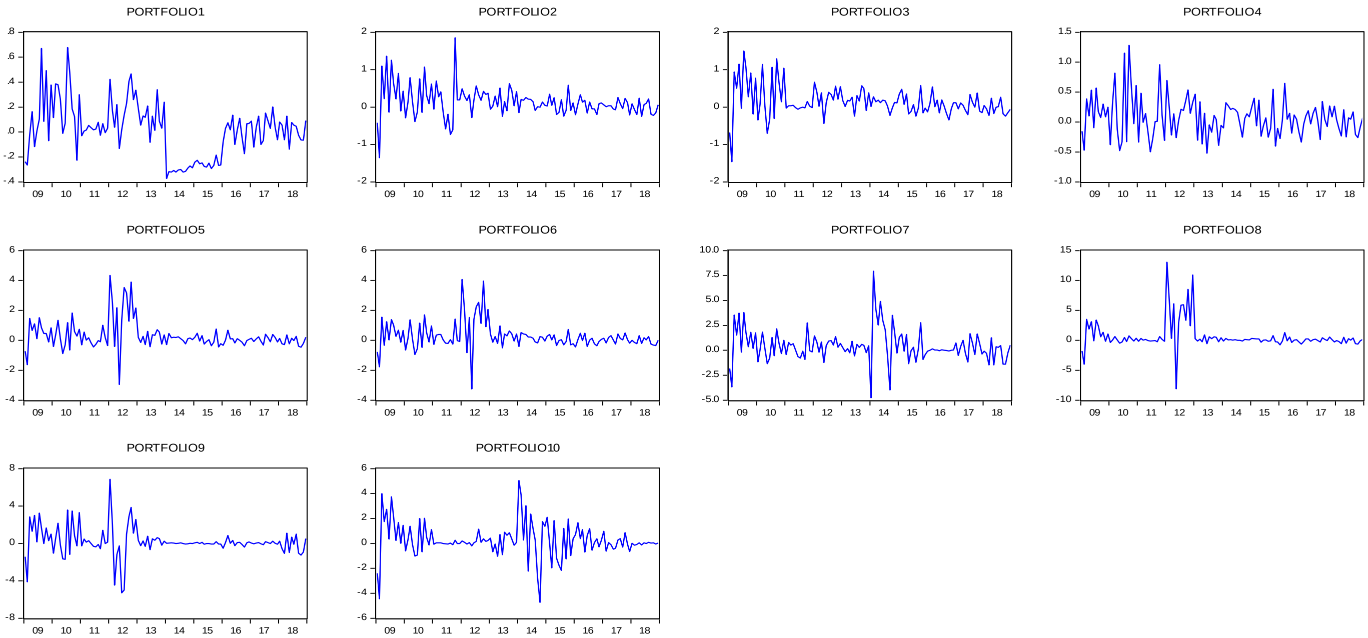


Figure 8 depicts the trend analysis above for the ten-unit trust portfolios in South Africa. Portfolios were sorted annually based on the standard deviations of returns

Trend analysis in finance or technical analysis is utilized with the aim of identifying patterns and information from historical data in order to make inferences about future movements in price (Brown & Jennings, 1989). As shown in Figure 8, mutual fund returns in South Africa have been quite volatile during the period under investigation. Portfolio performance can be assessed by looking at its average rate of return and its risk. The descriptive statistics were computed to have an overview of the unit trust portfolios in the period under investigation.

Over the period under investigation, portfolios 1 to 5 had the least volatility, and portfolios six to ten had the most volatility. Portfolio 1 has the lowest standard deviation and the lowest return over the period under observation. Portfolio 10 has a high standard deviation and a fairly average return relative to the other portfolios. It can be seen that portfolio 8 had the highest average return and the highest risk, this finding contradicts the bulk of the literature (Haugen & Heins (1972); Haugen & Baker (1991); Bollerslev, Tauchen & Zhou (2009); Baker & Haugen (2012); Anderson, Bianchi & Goldberg (2013) and Novy-Marx (2016)), which shows that portfolios with higher volatility of returns underperform their lower volatility counterparts.

In this study, portfolio 1 has the lowest standard deviation, but it also has the lowest returns over the period observed. In a recent study, however, Bu, Fu, and Jawadi (2019) observed that securities with a higher sensitivity to the volatility factor had higher returns than securities that a lower sensitivity to the volatility factor. When looking at the hedge fund performance relative to unit trusts in South Africa, unit trusts have a higher average return than the hedge fund portfolios. The highest average return for the unit trust portfolios was 0.62%, the hedge fund portfolio with the highest return had an average return of 0.01%. This finding contradicts the theory, although hedge funds have been found to underperform known benchmarks. Fung and Hsieh (1997) provided evidence that hedge funds outperformed mutual funds.

The ex-post Sharpe ratio looks at the historical performance of portfolios relative to the standard deviation or risk (Sharpe, 1994). Funds with a higher positive Sharpe ratio are attractive, and funds with a negative Sharpe ratio are unattractive. A negative Sharpe ratio indicates that excess returns are negative (McLeod & van Vuuren, 2004). During the period under investigation, the Sharpe Ratio of all the portfolios was positive, excluding portfolio one, which had a negative Sharpe ratio. Portfolio 10 had the highest Sharpe ratio, and portfolio 1 had the lowest Sharpe ratio. This finding suggests that portfolio 10 is the optimal portfolio; it has the highest risk-adjusted return and is suboptimal because the excess returns are negative.

4.2.1 Descriptive statistics

Table 10: Descriptive statistics – unit trusts

	Portfolio 1	Portfolio 2	Portfolio 3	Portfolio 4	Portfolio 5	Portfolio 6	Portfolio 7	Portfolio 8	Portfolio 9	Portfolio 10
Mean	0.018	0.136	0.141	0.076	0.299	0.263	0.432	0.621	0. 193	0.259
Standard deviation	0.219	0.401	0.405	0.326	0.936	0.879	1.597	2.309	1.513	1.374
Skewness	0.443	0.776	0.479	0.865	1.600	1.118	0.833	2.383	0.138	0.019
Kurtosis	3.231	7.119	5.850	4.530	8.931	9.281	7.619	14.672	8.549	6.209
Jarque-Bera Probability	0.123	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Sharpe ratio	-0.147	0.105	0.115	0.001	0.197	0.038	0.211	0.013	0.096	3.852

Table 10 above illustrates the descriptive statistics for the period under investigation. The Unit Trust portfolios, specifically under the equity general category, were placed into ten portfolios annually over the ten year period with portfolio one representing the portfolio with the lowest variability in returns and portfolio ten representing the portfolio with the highest variability. The mean is calculated, which represents the average return over the period. The standard deviation looks at the variability in portfolio returns over the period, and it captures risk. The skewness looks at the extent to which the returns of the portfolio move away from a normal distribution. The Sharpe Ratio is the excess returns per unit risk. Kurtosis looks at the tails of a distribution; in finance, this measure indicates risk. The Jarque-Bera statistic looks at the goodness of fit of the model; it tests that the skewness and kurtosis matches a normal distribution.

Both hedge funds and mutual funds in South Africa had positive Sharpe ratios for the period under investigation. When looking at the hedge fund portfolios relative to the mutual funds; the highest hedge fund Sharpe ratio (2.341) is lower than the highest mutual fund Sharpe ratio (3.852) in the South African context; this finding is surprising. Eling and Faust (2010) examined hedge funds and mutual funds in emerging markets: hedge fund returns were higher than mutual funds. Furthermore, it was illustrated that hedge funds outperformed mutual funds in poor and neutral market environments, whilst maintaining similar performance in favourable market environments.

Portfolios one to ten exhibit excess kurtosis, with kurtosis statistics significantly above 3. The Jarque-Bera probability for most of the portfolios is 0.00%, suggesting that the returns for the unit trust portfolios are non-normal. Observing skewness, Portfolio 10 is closely symmetrical while portfolios 5,6, and 8 are positively skewed and are less preferred because more of their distributions lie on the left side. This evidence suggests that the returns of mutual funds in South Africa are non-normal.

4.2.2 Unit trust regression results

In this section, we describe and explain the regression results of the unit trust portfolios. We start by the 2 by 2 sort, followed by the 2 by 3 and then lastly, the 2 by 2 by 2 sort.

Regression results are reported in Table 11. All Alphas for the portfolios are negative and statistically significant, except for portfolio 1. This is in line with a number of studies in literature, mutual funds have been found to have negative alphas when looking at the average returns (see Jensen, 1968); Elton et al. 1993; and Carhart, 1997). There has been evidence of mutual fund over-performance in the short-run; however, this persistence is not evident in the long run (Hendricks et al.,1993).

This finding has also been documented in another study by Bollen and Busse (2004). Some authors have also argued that over-performance in some funds will be levelled out by underperformance in the market (Fama & French, 2010). The hedge fund portfolios, however, had positive significant constants.

Table 11: The 2 * 2 Sorts Without Volatility Factor.

	portfolio1	portfolio2	portfolio3	portfolio4	portfolio5	portfolio6	portfolio7	portfolio 8	portfolio 9	portfolio 10
C	-0.055 (0.0426)	-0.175*** (0.0296)	-0.173*** (0.0303)	-0.174*** (0.0191)	-0.224*** (0.0616)	-0.261*** (0.0642)	-0.627*** (0.1446)	-0.307* (0.2197)	-0.656*** (0.1425)	-0.495*** (0.1285)
EXC RTNS	0.020*** (0.0040)	0.087*** (0.0058)	0.089*** (0.0059)	0.069*** (0.0071)	0.144*** (0.0196)	0.144*** (0.0199)	0.297*** (0.0282)	0.257*** (0.0676)	0.239*** (0.0345)	0.228*** (0.0251)
SIZE	0.276 (0.2382)	0.297 (0.3414)	-0.057676 (0.3499)	0.756* (0.3919)	2.601 (1.6080)	3.192** (1.3797)	2.244 (1.6689)	4.438 (4.9207)	-0.833 (2.8030)	-9.773*** (1.4833)
HML	-0.137 (0.1195)	-0.149 (0.1707)	0.028 (0.1750)	-0.377* (0.1962)	-1.304 (0.8052)	-1.596** (0.6907)	-1.126 (0.8347)	-2.225 (2.4637)	0.418 (1.4040)	4.882*** (0.7419)
MOM	0.137 (0.1191)	0.148 (0.1707)	-0.028 (0.1750)	0.378* (0.1959)	1.301 (0.8040)	1.595** (0.6899)	1.122 (0.8345)	2.218 (0.9179)	-0.416 (1.4015)	-4.886** (0.7417)
Adjusted R-Squared	0.1007	0.668	0.659	0.687	0.384	0.463	0.500	0.181	0.346	0.467
Durbin Watson	0.756	1.862	1.629	1.520	1.481	1.687	1.7113	1.628	1.444	1.755
Prob (Fstat)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

*Table 11 provides results of the regression outputs for the 10 models for which in the columns are portfolios from 1 to 10, and the rows are the different explanatory variables. Explanatory variables included in the models are the Market Excess Returns (EXC RTNS), Size Factor (SIZE), Value Premium Factor (HML), and Momentum Factor (MOM). The table also illustrates the adjusted R- squared, the Durbin Watson statistic, which tests for autocorrelation in the model and the F- Statistic, which illustrates the goodness of fit of the model. The problem of autocorrelation, if present in any model, was solved using the Newey- West specification, which allows for the standardization of the error terms. *, ** and *** respectively show that the reported coefficients are statistically significant at 1%, 5%, and 10% confidence levels.*

Performance of mutual fund managers has also been linked to luck and not to the individual skill of mutual fund managers (see, Wermers, 2000; Barras, Scaillet & Wermers, 2010; Busse, Goyal & Wahal, 2010). This is contradicted by Berk and Van Binsbergen (2015), who observed that mutual fund managers do have skills which, however, cannot be accounted for through alpha but rather through the value-added by managers. The performance of mutual funds and the generation of positive alpha has been a point of great debate.

A recent study by Huang, Pilbeam, and Pouliot (2019) looks at the performance of mutual funds and argues that over-performance can be found. This is in line with other studies that have observed over-performance in actively managed funds (see, Grinblatt & Titman, 1992; Cremers & Petajisto, 2009; Kremnitzer, 2012; Doshi, Amihud & Goyenko, 2013; and Doshi, Elkamhi & Simutin, 2015). In South Africa, Manjezi (2008) found that a significant number of mutual funds had a significant positive alpha, which is in contradiction of another study where evidence could not be found in favour of persistence (Mibiola, 2013). Consistent with the findings reported here, Nana (2012) could also not conclusively find evidence in favour of persistence in the South African context when looking at mutual funds.

The coefficients for the market risk premium (EXC RTNS) are positive and statistically significant. This implies that the market premium has a positive impact on returns. An increase in market premium increases the returns of the portfolio. This result confirms the result between systematic risk and returns. The value (HML) factor is significant in only three of the ten portfolios. In portfolios 4 and 6, it has a negative coefficient and a positive coefficient in portfolio 10. The momentum (MOM) factor is significant in explaining one portfolio of three of the ten portfolios. It has a positive coefficient in portfolio 4 and 6 and a large negative coefficient in portfolio 10.

The size (SIZE) factor is significant in three of the ten portfolios. In portfolios 4, 6, and 10, it has a positive coefficient suggesting a small-cap tilt in the portfolios. Some of the results are consistent with literature others are not. Results from asset pricing models differ from country to country; findings depend on the type market and dominant risk exposures (Tony-Okeke, 2015). Fama and French (2012) documented an insignificant size premium in the international developed regions examined. When looking at emerging markets: in the Hanauer and Linhart (2015) study, the emerging market global portfolio had an insignificant size factor. Furthermore, two of the four emerging market regions in the study had significant size premiums.

Tony-Okeke (2015) assessed the performance of multifactor asset pricing models in the South African context. The study considered the three-factor and four-factor model adjusted for illiquidity. When looking at the four-factor model, the value factor (HML) was found to be insignificant whilst the size momentum and illiquidity factors were found to be significant. Small and Hsieh (2017) utilized the Carhart (1997) model to assess risk exposures on the financial and industrial stocks in South Africa. It was found that the financial sector had significant exposure to risk, and the industrial sector illustrated exposure to size momentum and value.

In developed markets when looking at stock returns the value and momentum factors are significant in explaining portfolio returns: Fama and French (2012) examined the impact of the size, value and momentum factors across different regions and reported significant value and momentum premiums in three of the four regions examined. Cakici, Fabozzi, and Tan (2013) examined the size, value, and momentum factors in emerging market stock returns and found a negative correlation between emerging market returns and the value and momentum factor. In contrast, Hanauer and Linhart (2015) documented a significant positive value factor in the emerging markets examined. Furthermore, when looking at the momentum factor, Hanauer and Linhart (2015) documented a positive significant momentum factor when looking at global emerging markets and an insignificant momentum factor in the specific emerging market regions.

Table 12 : The 2 * 2 Sorts With the Volatility Factor.

	portfolio 1	portfolio 2	portfolio 3	portfolio 4	portfolio 5	portfolio 6	portfolio 7	portfolio 8	portfolio 9	portfolio 10
C	-0.049 (0.0459)	-0.230*** (0.0339)	-0.206*** (0.0356)	-0.187*** (0.2767)	-0.288** (0.1116)	-0.312*** (0.0803)	-0.491*** (0.1706)	-0.427* (0.2197)	-0.763*** (0.1455)	-0.579*** (0.1524)
EXC RTNS	0.0188 (0.0046)	0.097*** (0.0065)	0.095*** (0.0068)	0.071*** (0.0053)	0.156*** (0.0214)	0.153*** (0.0227)	0.271*** (0.0327)	0.279*** (0.0676)	0.260*** (0.0356)	0.243*** (0.0292)
SIZE	0.260 (0.2469)	0.444 (0.3328)	0.032 (0.3504)	0.788*** (0.2720)	2.771** (1.0969)	3.325** (1.4041)	1.887 (1.6779)	4.754 4.9208)	-0.550 (2.822)	-9.552*** (1.4986)
HML	-0.130 (0.1238)	-0.223 (0.1665)	-0.017 (0.1752)	-0.394*** (0.1361)	-1.389** (0.5486)	-1.663** (0.7028)	-0.948 (0.8392)	-2.383 (2.4637)	0.277 (1.4136)	4.772*** (0.7495)

MOM	0.130 (0.1234)	0.222 (0.1664)	0.016 (0.1752)	0.394*** (0.1360)	1.386** (0.5484)	1.662** (0.7020)	0.943 (0.8389)	2.377 (2.4604)	-0.274 (1.4110)	-4.776*** (0.7493)
LVH	-0.052 (0.1133)	0.502*** (0.1627)	0.304* (0.1713)	0.112 (0.1329)	0.577 (0.5362)	0.455 (0.3068)	-1.211 (0.8202)	1.074 (0.9168)	0.962* (0.5073)	0.751 (0.7327)
Adjusted R-Squared	0.093	0.691	0.665	0.687	0.384	0.463	0.505	0.178	0.323	0.467
Durbin Watson	0.7502	1.756	1.598	1.526	1.460	1.660	1.690	1.616	1.438	1.710
Prob (F-stat)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

*Table 12 provides results of the regression outputs for the 10 models for which in the columns are portfolios from 1 to 10, and the rows are the different explanatory variables. Explanatory variables included in the models are the Market Excess Returns (EXC RTNS), Size Factor (SIZE), Value Premium Factor (HML), and Momentum Factor (MOM). The volatility factor (LVH) The table also illustrates the adjusted R- squared, the Durbin Watson statistic, which tests for autocorrelation in the model and the F- Statistic, which illustrates the goodness of fit of the model. The problem of autocorrelation, if present in any model, was solved using the Newey- West specification, which allows for the standardization of the error terms. *, ** and *** respectively show that the reported coefficients are statistically significant at 1%, 5%, and 10% confidence levels.*

As shown in Table 12, adding the volatility factor (LVH) to the unit trust 2 by 2 portfolios impacted the portfolio alphas (constant). While the alphas for portfolios 2 to 10 remained significant, their magnitudes worsened. With the volatility augmented model, the unit trust alpha component of returns reduced. However, portfolio 7 alpha improved from -0.627 to -0.427. These findings are in agreement with some studies, such as Jordan and Riley (2015), which found that the addition of the volatility factor did worsen the alphas of mutual funds: in their study, alpha either became insignificant or close to zero. In the same volatility, augmented unit trust models, the market risk premium factor (EXC RTNS) remained positive and statistically significant. This is in line with theoretical expectations.

As the equity risk premium increases, the overall return of underlying portfolios also increases. The SIZE factor is only significant in portfolios 4, 5, 6, and 10. The MOM factor in this volatility augmented model is significant in explaining portfolios 4, 5, 6, and 10. In portfolios 4, 5, and 6, it has a positive significant impact, while in portfolio 10, it has a negative significant impact. Emerging markets have been found to have higher transaction expenses and fewer market participants relative to emerging markets. Characteristics unique to emerging markets can have an impact on value and momentum outcomes when looking at the cross-sectional variation in returns (Cakici, Tang & Yan, 2016).

As illustrated in Table 12, the volatility factor is only significant in three out of the ten portfolios, and this finding contrasts some recent studies which have found that the volatility factor is both significant and negative (Agarwal et al., 2017; Hollstein & Prokopczuk, 2018; and Ruan, 2019). These studies report findings suggesting that volatility is not a significant factor in the pricing of mutual fund returns. Kaeck (2018) also provided evidence that volatility is a significantly priced risk factor. Surprisingly, although the volatility factor is not significant for the 2*2 portfolios in this study, the addition of the factor improved the model, which was expected. Incorporating the volatility factor in multifactor models improves the explanatory capacity of the model (Jordan & Riley, 2015).

The contradiction in results could emanate from the construction of the volatility factor. Jordan and Riley (2015) constructed the volatility factor by taking the low volatility securities from the highly volatile securities. Hollstein and Prokopczuk (2018) and Ruan (2019) constructed the volatility factor using the Chicago Board Options Exchange (CBOE) Volatility Index (VIX) as a proxy for volatility. In this study, the volatility factor is constructed from the payoff of a synthetic one month at the money put and call options on the JSE Index following, similar to the methodology used in Ang et al. (2006).

The three portfolios that did, however, have a significant volatility factor, had a positive coefficient for the factor which contradicts other studies. Ang et al. (2006) looked at the volatility factor and found that it has significant negative exposure to returns. This finding was also observed by Hollstein and Prokopczuk (2018) and Ruan (2019).

Overall, the evidence from this study suggests that the volatility factor does not have a significant impact on the unit trust portfolio returns in the South African context when looking at the 2 by 2 portfolio sorts. This finding contradicts findings in the hedge fund section. When looking at the volatility augmented models, of the six hedge fund portfolios, three had positive and statistically significant volatility factors.

*The 2 * 3 sort without volatility factor*

Table 13 : The 2 * 3 sort without volatility factor

	portfolio 1	portfolio2	portfolio3	portfolio4	portfolio5	portfolio6	portfolio7	portfolio 8	portfolio 9	portfolio 10
C	-0.018 (0.0444)	-0.197*** (0.0357)	-0.147*** (0.0348)	-0.222*** (0.0293)	-0.216* (0.1200)	-0.246* (0.1072)	-0.766*** (0.1805)	-0.070 (0.3349)	-0.694*** (0.1461)	-0.557*** (0.1787)
EXC RTNS	0.009 (0.0078)	0.095*** (0.0094)	0.077*** (0.0092)	0.088*** (0.0077)	0.149*** (0.0317)	0.147*** (0.0283)	0.333*** (0.0476)	0.191** (0.0884)	0.258*** (0.0434)	0.221*** (0.0472)
SIZE	0.259** (0.1149)	-0.301* (0.1688)	-0.054 (0.1645)	-0.286** (0.1386)	0.358 (0.5679)	0.397 (0.5068)	-0.898 (0.8538)	2.397 (1.5836)	-1.272* (0.7300)	--1.786** (0.8451)
HML	- 0.175*** (0.0560)	0.032 (0.0727)	-0.031 (0.0709)	0.062 (0.0597)	-0.283 (0.2447)	-0.331 (0.2184)	0.671* (0.3678)	-1.168* (0.6823)	-0.231 (0.2471)	0.713** (0.3641)
MOM	-0.000 (0.0942)	-0.229* (0.1288)	-0.555*** (0.1255)	0.189* (0.105776)	0.458 (0.4334)	0.414 (0.3867)	-0.327 (0.651)	0.717 (1.2085)	-1.1847* (0.6756)	-2.007*** (0.6450)
Adjusted R-Squared	0.1494	0.6941	0.716	0.687	0.365	0.427	0.507	0.189	0.406	0.348
Durbin Watson	0.8347	1.833	1.585	1.567	1.421	1.595	1.691	1.571	1.358	1.846
Prob (Fstat)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

*Table 13 provides results of the regression outputs for the 10 models for which in the columns are portfolios from 1 to 10, and the rows are the different explanatory variables. Explanatory variables included in the models are the Market Excess Returns (EXC RTNS), Size Factor (SIZE), Value Premium Factor (HML), and Momentum Factor (MOM). The table also illustrates the adjusted R- squared, the Durbin Watson statistic, which tests for autocorrelation in the model and the F- Statistic, which illustrates the goodness of fit of the model. The problem of autocorrelation, if present in any model, was solved using the Newey- West specification, which allows for the standardization of the error terms. *, ** and *** respectively show that the reported coefficients are statistically significant at 1%, 5%, and 10% confidence levels.*

In this section, the impact of the volatility factor to the 2 by 3 sort is analyzed. As before, the models are run, excluding the volatility factor and then including the volatility factor. This is done to ascertain the impact caused by the introduction of the volatility factor to the portfolio alphas and to see whether the volatility factor is significant in explaining unit trust returns.

Table 13 reports the results obtained from running 10 models from portfolio 1 to 10, respectively. From the table, it can be observed that all portfolio alphas have negative coefficients just like in the 2 by 2 sort. All of the alphas are statistically significant, except for portfolio 1 and 8. The EXC RTNS variable, which is the risk premium, has positive coefficients throughout the portfolios and is statistically significant except in portfolio 2. The SIZE factor is statistically significant in portfolios 1, 2, 4, 9, and 10. The HML factor is statistically significant in explaining portfolios 1,7,8, and 10. The MOM factor is significant in explaining portfolios 2, 3, 4, 9, and 10.

*The 2 * 3 Sort with Volatility*

Table 14 : The 2 * 3 sort with a volatility factor

	portfolio1	portfolio2	portfolio3	portfolio4	portfolio5	portfolio6	portfolio7	portfolio 8	portfolio 9	portfolio 10
C	-0.009 (0.0457)	-0.241*** (0.0393)	-0.167*** (0.0391)	-0.229*** (0.0331)	-0.268** (0.1352)	-0.277** (0.1209)	-0.614** (0.2015)	-0.179 (0.3776)	-0.747*** (0.1502)	-0.670*** (0.2005)
EXC RTNS	0.008 (0.0093)	0.103*** (0.0099)	0.081*** (0.0098)	0.089*** (0.0083)	0.159*** (0.0339)	0.153*** (0.0303)	0.304*** (0.0506)	0.212** (0.0947)	0.269*** (0.0452)	0.243*** (0.0502)
SIZE	0.254** (0.1237)	-0.277* (0.1655)	-0.043 (0.1646)	-0.283** (0.1393)	0.386 (0.5696)	0.414 (0.5091)	-0.981 (0.8490)	2.456 (1.5906)	-0.243* (0.7220)	-1.725** (0.8447)
HML	-0.174*** (0.1237)	0.0316 (0.0712)	-0.032 (0.07078)	0.062 (0.0599)	-0.284 (0.2450)	-0.331 (0.2190)	0.673* (0.3651)	-1.170* (0.6841)	-0.233 (0.2457)	0.711** (0.3632)
MOM	-0.010 (0.1133)	-0.185 (0.1273)	-0.535*** (0.1266)	0.196* (0.1072)	0.509 (0.4382)	0.446 (0.3916)	-0.477 (0.6531)	0.824 (1.2235)	-1.133* (0.6807)	-1.896*** (0.6498)
LVH	-0.087 (0.1207)	0.393** (0.1591)	0.182 (0.1582)	0.064 (0.1340)	0.460 (0.5477)	0.280 (0.4895)	-1.344 (0.8162)	0.962 (1.5293)	0.468 (0.4189)	0.999 (0.8121)
Adjusted – R Squared	0.144	0.707	0.7169	0.698	0.364	0.423	0.515	0.185	0.402	0.351
Durbin Watson	0.832	1.737	1.582	1.570	1.402	1.578	1.662	1.557	1.356	1.798
Prob (F-Stat)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

*Table 14 provides results of the regression outputs for the 10 models for which in the columns are portfolios from 1 to 10, and the rows are the different explanatory variables. Explanatory variables included in the models are the Market Excess Returns (EXC RTNS), Size Factor (SIZE), Value Premium Factor (HML), and Momentum Factor (MOM). The volatility factor is (LVH). The table also illustrates the adjusted R- squared, the Durbin Watson statistic, which tests for autocorrelation in the model and the F- Statistic, which illustrates the goodness of fit of the model. The problem of autocorrelation, if present in any model, was solved using the Newey- West specification, which allows for the standardization of the error terms. *, ** and *** respectively show that the reported coefficients are statistically significant at 1%, 5%, and 10% confidence levels.*

In this volatility augmented model (Table 14), the coefficients of alphas 2, 3, 4, 5, 6, 7, 9, and 10 are still statistically significant as before. The inclusion of the volatility factor LVH did change the values of portfolio alphas. All alphas are still negative. The coefficients of significant alphas worsened with the inclusion of the volatility factor. This statistical evidence shows that the inclusion of LVH into the unit trust 2 by 3 sort models worsens the intercept component of returns. The volatility factor is only significant to Portfolio 2. In that respective portfolio, it has a positive coefficient and is significant at 5%, and this finding is consistent with the 2 by 2 portfolio sort.

However, many coefficients of LVH are still not significant. This evidence suggests that the volatility factor does not have a significant impact on the unit trust portfolio returns when looking at the 2 by 3 portfolio sort. The EXC RTNS variable is still positive and statistically significant in the same portfolios as before. The inclusion of the volatility factor did not change much on SIZE, HML, and MOM with the coefficients much more the same as before.

*The 2 * 2 * 2 sort without Volatility factor*

The table below shows the outputs of models that were run using the 2 by 2 by 2 sorts without the volatility factor.

Table 15: The 2* 2*2 sort without the volatility factor

	portfolio1	portfolio2	portfolio3	portfolio4	portfolio5	portfolio6	portfolio7	portfolio 8	portfolio 9	portfolio 10
C	-0.046 (0.5555)	-0.154*** (0.0319)	-0.151*** (0.0309)	-0.146*** (0.0250)	-0.259** (0.1029)	-0.273*** (0.0910)	-0.760*** (0.1553)	-0.517* (0.2854)	-0.401** (0.1629)	-0.425*** (0.1372)
EXC RTNS	0.022*** (0.0037)	0.080*** (0.0068)	0.089*** (0.0066)	0.066*** (0.0053)	0.150*** (0.0219)	0.145*** (0.0193)	0.319*** (0.0330)	0.290*** (0.0607)	0.197*** (0.0035)	0.240*** (0.0292)
SIZE	0.544 (0.3594)	0.052 (0.3123)	0.442 (0.3024)	0.022 (0.2452)	2.269** (1.0080)	2.352*** (0.8914)	3.442** (1.5206)	7.152** (2.7948)	-0.773 (1.5949)	-4.763*** (1.3439)
HML	-0.366*** (0.1071)	-0.197 (0.1656)	-0.614*** (0.16038)	-0.462*** (0.1300)	-0.332 (0.5346)	-0.662 (0.4727)	0.552 (0.8064)	0.516 (1.4822)	-3.348*** (0.8458)	-0.346 (0.7123)
MOM	-0.382** (0.1958)	0.448 (0.2794)	-0.745*** (0.2706)	-0.119 (0.2195)	0.233 (0.9020)	0.258 (0.7976)	-0.020 (1.361)	0.360 (2.5010)	-1.126 (1.4272)	-4.998*** (1.2025)
Adjusted – R Squared	0.156	0.680	0.706	0.700	0.388	0.458	0.523	0.228	0.414	0.496
Durbin Watson	0.7412	1.840	1.626	1.405	1.46	1.662	1.638	0.626	1.431	1.602
Prob (F-Stat)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

*Table 15 provides results of the regression outputs for the 10 models for which in the columns are portfolios from 1 to 10, and the rows are the different explanatory variables. Explanatory variables included in the models are the Market Excess Returns (EXC RTNS), Size Factor (SIZE), Value Premium Factor (HML), and Momentum Factor (MOM). The table also illustrates the adjusted R- squared, the Durbin Watson statistic, which tests for autocorrelation in the model and the F- Statistic, which illustrates the goodness of fit of the model. The problem of autocorrelation, if present in any model, was solved using the Newey- West specification, which allows for the standardization of the error terms. *, ** and *** respectively show that the reported coefficients are statistically significant at 1%, 5%, and 10% confidence levels.*

Just like in the 2 by 2 and 2 by 3 sorts, the alphas of all the portfolios are negative and statistically significant. This excludes the alpha of portfolio 1, which is negative but not statistically significant. The market risk premiums EXC RTNS has positive and statistically significant coefficients in all the 10 portfolios by 2 by 2.The SIZE factor is significant in portfolios 5,6,7,8, and 10. The HML factor is statistically significant in explaining portfolios 1, 3, 4, and 9. The MOM factor is significant in explaining portfolios 1, 3 and 10.

*The 2 *2 * 2 sort with volatility*

Table 16: The 2* 2*2 sort with the volatility factor

	portfolio1	portfolio2	portfolio3	portfolio4	portfolio5	portfolio6	portfolio7	portfolio 8	portfolio 9	portfolio 10
C	-0.036 (0.0567)	-0.214*** (0.0375)	-0.186*** (0.0371)	-0.144*** (0.0304)	-0.335*** (0.1245)	-0.323*** (0.1104)	-0.639*** (01877)	-0.728** (0.3452)	-0.459** (0.1978)	-0.556*** (0.1654)
EXC RTNS	0.019*** (0.0046)	0.0916*** (0.0078)	0.096*** (0.0077)	0.065*** (0.0063)	0.1644*** (0.0258)	0.155*** (0.0118)	0.296*** (0.0388)	0.331*** (0.0714)	0.208*** (0.041)	0.266*** (0.0342)
SIZE	0.522 (0.3612)	0.192 (0.3071)	0.525* (0.3038)	0.019 (02495)	2.448** (1.0257)	2.467*** (09044)	3.161** (1.5384)	7.643*** (2.829)	-0.638 (1.621)	-4.460*** (1.3558)
HML	-0.374*** (0.1098)	-0.146 (0.1617)	-0.584*** (0.1600)	-0.463*** (0.1315)	-0.267 (0.5375)	-0.620 (0.4764)	0.449 (0.8104)	0.696 (1.4903)	-3.298*** (0.8540)	-0.234 (0.7142)
MOM	-0.373* (0.1981)	0.393 (0.2719)	-0.779*** (0.2690)	-0.117 (0.2210)	0.161 (0.9036)	0.211 (0.8010)	0.093 (1.3624)	0.163 (2.5056)	-1.1801 (1.4356)	-5.120*** (1.2007)
LVH	-0.072 (0.1006)	0.463*** (0.1627)	0.276* (0.1610)	-0.012 (0.1322)	0.590 (0.5407)	0.382 (0.4792)	-0.932 (0.8151)	1.628 (1.4991)	0.447 (0.8589)	1.005 (0.7184)
Adjusted – R Squared	0.151	0.689	0.712	0.698	0.390	0.456	0.524	0.229	0.4111	0.501
Durbin Watson	0.741	1.699	1.582	1.404	1.438	1.632	1.630	1.599	1.446	1.544
Prob (F-Stat)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

*Table 16 provides results of the regression outputs for the 10 models for which in the columns are portfolios from 1 to 10, and the rows are the different explanatory variables. Explanatory variables included in the models are the Market Excess Returns (EXC RTNS), Size Factor (SIZE), Value Premium Factor (HML), and Momentum Factor (MOM). The volatility factor is (LVH). The table also illustrates the adjusted R- squared, the Durbin Watson statistic, which tests for autocorrelation in the model and the F- Statistic, which illustrates the goodness of fit of the model. The problem of autocorrelation, if present in any model, was solved using the Newey- West specification, which allows for the standardization of the error terms. *, ** and *** respectively show that the reported coefficients are statistically significant at 1%, 5%, and 10% confidence levels.*

It was included in the previous model to see its impact on the portfolio alphas and the portfolio returns in particular in order to capture the impact of the volatility factor. The alpha coefficients of all portfolios are still negative and statistically significant, except for portfolio 1. This solidifies the fact that the unit trust fund managers have been underperforming the market in the period under investigation. The inclusion of the volatility factor led to a decrease in the constant of 8 of the mutual fund portfolios. The value of the portfolio alphas changed marginally with the inclusion of the volatility factor similar to the other sorts.

The volatility factor was only significant in two of the ten portfolios. This evidence suggests that the volatility factor does not have a significant impact on the unit trust portfolio returns, and this finding is consistent with the 2 by 2 and 2 by 3 portfolio sorts. The EXC RTNS factor is still positive and statistically significant in all the 10 portfolios under examination. This finding is similar to the 2 by 2 and 2 by 3 sorts. Such proves the fact that the EXC RTNS is an important factor in explaining the unit trust portfolio returns in South Africa.

Chapter V: Conclusion

The study of the low volatility anomaly has gained much attention over the years (see Haugen,and Heins, 1972; Baker, 1991; Baker and Haugen, 2012; Blitz et al., 2013). However, the implications of the volatility anomaly and its impact on the expected returns of mutual funds and hedges are largely unknown when looking at the South African context. The potential impact of the low volatility anomaly in the investment industry needs to be addressed from an academic and an industrial perspective in South Africa.

This design is utilized in the study, and assessed if volatility is priced in the South African context. The models selected in this study aim to answer the questions addressed in the literature section. The literature review section addresses literature from different aspects of the world. The purpose of the review to analyze and understand the various bodies of research that surround the low volatility pricing anomaly and how this anomaly impacts both hedge and mutual funds. The study enabled the researcher to gain a better understanding of the low volatility anomaly. The review enabled the researcher to gain insight from a global perspective by examining concepts, findings, and theories; this has helped enhance research when looking at the South African context.

5.1 Summary of Results

Volatility is an essential factor in financial markets; it has important implications for portfolio formation, pricing, and returns (Jordan & Riley, 2015). Volatility indicates the dispersion of stocks, and the standard deviation for security has been utilized as an indicator of risk (Markowitz, 1952).

The introduction of the volatility factor in the hedge fund models increased most of the hedge fund alphas. The alphas of AFII, ALSI, AMNI, AMSI, and ASMI all improved with the introduction of the volatility factor. Of these indexes, only the alpha of AFII was not significant. The results suggest that volatility is a significant determinant in the pricing of hedge funds in South Africa, which is in line with some studies (see, Agarwal et al., 2017; and Blitz, 2018).

The coefficients of the volatility factor in the hedge fund models were positive which contradicts the study by Dash and Moran (2005), Agarwal et al., (2017), and Blitz, (2018) suggesting that, during the study period, South African Hedge Fund Managers were "betting on volatility." Evidence from the modelling shows that the volatility factor has a positive and significant impact on the hedge fund returns in South Africa. As seen in the sample hedge fund indexes, the volatility factor has a positive and significant impact on four out of six of them, namely, ALSI, AMNI, AMSI, and ASMI. This suggests that increases in the volatility of returns increase the hedge fund returns in South Africa, holding all other variables constant. This confirmed a higher risk higher return trade-off. This finding also contradicts a South African study by Momoza (2017), who found a negative impact running from the volatility factor to the returns of various hedge fund strategies.

The coefficient of determination (R squared) for the volatility augmented models was higher than it was for models without volatility. This suggests that the inclusion of the volatility factor into hedge fund models increases the predictive power of the models. In this study, the volatility augmented hedge funds models explain the hedge fund returns better than models without volatility. The inclusion of the volatility factor in Jordan and Riley (2015) also improved models in the study.

As seen in the unit trust section, the ten volatility sorted returns were modelled using three sorts, namely the 2 by 2 sorts, 2 by 3 sorts, and the 2 by 2 by 2. This was done for triangulation. The regression results showed that the addition of the volatility factor does not increase the alpha of the unit trust portfolios, which contradicts previous studies. Across sorts, the inclusion of the volatility factor saw the alpha of portfolios reduce significantly. The coefficients of most of the volatility factors across the 2 by 2, 2 by 3, and the 2 by 2 by 2 were not significant. This finding was surprising when looking at other studies, Ang, Hodrick, King, and Zhang (2006), for example, assessed the volatility factor and its impact on returns; the element was found to be negative and significant in explaining returns.

Based on the results of the study, the volatility factor does not significantly explain unit trust returns in South Africa. It can be implied that the volatility factor does not inform unit trust returns in South Africa. The inclusion of the volatility factor did not improve the R-Squared of most of the unit trust models; the R-Squared remained relatively the same. This study concluded that the volatility factor is a significant determinant of the hedge fund returns in South Africa. The volatility factor augmented hedge fund models showed a higher predictive power than models without volatility.

The study found that the volatility factor does not have any significant impact on most of the unit trust returns by looking at the unit trusts. The volatility factor was not significant in explaining the unit trust returns. The coefficient of determination (R squared) for the volatility augmented model did not change significantly from the model without volatility, and the volatility factor was largely insignificant across the sorts

5.2 Limitations

Sample size: Compared to developed countries, the South African Mutual Fund and Hedge Fund Industries are relatively smaller in format. Furthermore, for mutual funds, the study focuses on the equity-only portion of the mutual funds' industry in South Africa. Smaller sample size has been found to reduce the explanatory power of the research.

Data collected: When looking at the hedge fund aspect of the research data, the amount and quality of data proved to be a significant limitation. Hedge funds do not trade publicly. Data in the South African context is available from one data vendor.

Time constraints: The study is to be completed within a year; there is a limited time to conduct the research.

Accessibility of data: In the South African context, specifically looking at the hedge fund and derivatives markets, data is difficult and expensive to access.

5.3 Recommendations for further research

When looking at the mutual fund section, future studies could utilize better models. Tony-Okeke (2015) examined the performance of multifactor models in the South African context. The model adjusted for an illiquidity premium was found to perform significantly better than the model without. The construction of the volatility factor may be improved or modified in the South African context. The hedge fund section utilized median returns from the various hedge fund strategies. Company-specific monthly returns would be more appropriate. Future studies could also use more powerful models that improve the explanatory power of the model. Cephas (2013) employed a nine-factor model in the South African hedge fund market context. The model had an explanatory power of seventy percent.

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Appendix A Hedge Fund Strategies in South Africa

Equity long/short	Funds aim to generate positive returns by being simultaneously long and short in the equity market. Market risk is reduced while company-specific risk is retained. The majority of local equity long/short funds tend to be long biased. An investing strategy of taking long positions in stocks that are expected to appreciate and short positions in stocks that are expected to decline. A long/short equity strategy seeks to minimise market exposure, while profiting from stock gains in the long positions and price declines in the short positions
Equity Neutral	Funds take similar sized long and short positions in related equity sectors with the effect that directional market risk is offset. A strategy undertaken by a manager that seeks to profit from both increasing and decreasing prices. Market-neutral strategies are often attained by taking matching long and short positions in different stocks to benefit from mispricing and delivering positive returns from both the long and short stock selections and reducing risk from movements in the broad market.
Fixed Income	An investment strategy that attempts to profit from arbitrage opportunities in interest rate securities. When using a fixed income a strategy, the investor assumes opposing positions in the market to take advantage of small price discrepancies while limiting interest rate risk. This general strategy type includes basis (e.g. cash vs. futures), yield-curve and credit spread trading, as well as volatility arbitrage.
Statistical arbitrage	Quantitative models are used to identify market opportunities and establish short-term positions involving a large number of securities
Volatility arbitrage	Funds aim to exploit mispricing between similar instruments where the mispricing is the result of different volatility assumptions by price makers.
Multi-strategy	An investment philosophy allocating investment capital to a variety of investment strategies and potentially across several asset classes.

Source: Novare Hedge Fund Survey 2017

Appendix B – Descriptive Statistics

Descriptive Statistics – Hedge Funds

	AFII	AIDI	ALSI	AMNI	AMSI	ASMI	BOND	BSPREAD	BTREND	CTREND	EQUITY	ESPREAD	FTREND
Mean	0.008774	0.009640	0.008163	0.006040	0.007314	0.007387	0.001960	-0.000317	-0.034738	-0.015238	0.087366	0.012066	-0.032730
Median	0.008100	0.009750	0.008650	0.006000	0.007200	0.008150	0.002658	0.000450	-0.074000	-0.049000	0.087150	0.020900	-0.076500
Maximum	0.024600	0.014500	0.046500	0.020500	0.030000	0.024400	0.149059	0.005300	0.505000	0.428700	0.096000	0.053000	0.691000
Minimum	-0.004200	0.002500	-0.038400	-0.021100	-0.019200	-0.009900	-0.073620	-0.008400	-0.266300	-0.246500	0.077700	-0.104800	-0.318100
Std. Dev.	0.005155	0.001851	0.013720	0.005471	0.008570	0.006235	0.030949	0.003085	0.153301	0.143903	0.004350	0.028271	0.182899
Skewness	0.394267	-0.555156	-0.292072	-0.809746	-0.182532	-0.191708	0.871608	-0.655536	1.323995	0.893459	-0.097176	-2.536018	1.337720
Kurtosis	3.588262	4.269358	3.643255	7.627275	3.373943	3.889536	6.613466	2.738104	4.561307	3.460486	2.282445	9.898584	5.047749
Jarque-Bera	4.839192	14.22031	3.775001	120.1721	1.365525	4.691408	80.47968	8.937493	47.24766	17.02560	2.763286	366.5800	56.75625
Probability	0.088958	0.000817	0.151450	0.000000	0.505219	0.095780	0.000000	0.011462	0.000000	0.000201	0.251166	0.000000	0.000000
Sum	1.052900	1.156800	0.979600	0.724800	0.877700	0.886400	0.235154	-0.038000	-4.168500	-1.828600	10.48390	1.447900	-3.927600
Sum Sq. Dev.	0.003162	0.000408	0.022402	0.003562	0.008740	0.004626	0.113983	0.001133	2.796636	2.464244	0.002252	0.095109	3.980789
Observations	120	120	120	120	120	120	120	120	120	120	120	120	120

Descriptive Statistics – Unit Trusts

	PORTFOLIO1	PORTFOLIO2	PORTFOLIO3	PORTFOLIO4	PORTFOLIO5	PORTFOLIO6	PORTFOLIO7	PORTFOLIO8	PORTFOLIO9	PORTFOLIO10
Mean	0.017855	0.135955	0.140761	0.075571	0.298970	0.263149	0.432056	0.621337	0.192753	0.258611
Median	0.029394	0.102380	0.069403	0.065412	0.112907	0.071410	0.200707	0.097361	0.035673	0.072151
Maximum	0.678440	1.850263	1.498322	1.281434	4.342789	4.062392	7.928121	13.04045	6.857643	5.037859
Minimum	-0.373196	-1.351798	-1.462330	-0.520424	-2.944609	-3.251176	-4.740680	-8.073083	-5.292655	-4.729481
Std. Dev.	0.219837	0.400741	0.405397	0.325367	0.935976	0.878908	1.597235	2.308906	1.513471	1.374627
Skewness	0.442500	0.775647	0.479485	0.865219	1.600273	1.117604	0.832861	2.383807	0.137780	0.019144
Kurtosis	3.231055	7.118718	5.850259	4.529504	8.931055	9.281091	7.618898	14.67159	8.549405	6.208515
Jarque-Bera	4.183052	96.85175	45.21800	26.66899	227.1046	222.2413	120.5443	794.7806	154.3591	51.48016
Probability	0.123499	0.000000	0.000000	0.000002	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Sum	2.142546	16.31462	16.89129	9.068533	35.87635	31.57792	51.84670	74.56046	23.13036	31.03336
Sum Sq. Dev.	5.751086	19.11060	19.55723	12.59777	104.2502	91.92499	303.5879	634.3948	272.5809	224.8622
Observations	120	120	120	120	120	120	120	120	120	120