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Optimal composition of hedge fund replicators in South Africa

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Abstract

The purpose of this paper was to explore the passive replication of hedge fund returns as an alternative means of investment. Current popular techniques have generally shown poor out-of-sample performance. This research aimed at creating an equity factor model through the use of the “style engine” created in Muller and Ward (2013). The sample hedge funds were used to create both single period and multi period rolling window portfolios of styles. The model was able to portray the investment styles of the selected samples and imitated the in-sample performance well. However, many of the out-of-sample clones showed severe under performance and suffered systematic breaks.

Keywords: Hedge Funds, Replication, Factor Styles, Systematic Risk, Smart Beta

Declaration

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

David Winson Boers

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Abbreviations

HNALSI	- Hedge News Africa Long Short Index
JSE	- Johannesburg Stock Exchange
RIF	- Retail Investor Fund
QIF	- Qualified Investor Fund
ANOVA	- Analysis of Variance
ETF	- Exchange-traded Fund
OTC	- Over-the-counter
CISCA	- Collective Investment Schemes Control Act

Chapter 1 – Introduction

1.1 The Research Problem

Over the last decade, the global economy has experienced a string of events which have led to difficult trading conditions for financial markets. From the liquidity crunch which squeezed interbank lending, to the crash of the US housing market and then the related international banking industry fallout. The consequential global economic downturn has driven institutional investors to be ever more diligent in their pursuit of available returns. And thus fuelling their interest in alternative assets such as hedge funds which promise the required returns in order to fulfil their fiduciary obligations in this low return environment (Fischer, Hanauer, & Heigermoser, 2016).

1.2 Background to Hedge Funds

So what exactly are hedge funds? Hedge Funds, as an investment mechanism, are a relatively recent development. Although they originally emerged in the 1950s, it wasn't until 1966 that the term was coined in a Fortune magazine article. "Hedge fund" was used to describe the investment philosophy of Alfred Winslow Jones, considered today as the father of the hedge fund industry (Brown & Goetzmann, 2001).

His fund displayed two key innovations. Firstly, it was "market neutral". This meant that the long positions of his undervalued stocks were funded in part by taking short positions in stocks that were overvalued. This allowed his fund to leverage large bets with much smaller initial investments. His second innovation was the introduction of the now well-known 20% fee on realised profits which he attributed to the ancient tradition of Phoenician sea captains who kept a fifth of the profits from successful voyages (Brown & Goetzmann, 2001).

Although investment philosophies of hedge funds today have evolved beyond Jones' "market neutral" strategy, funds continue to leverage and charge fees in almost exactly the same way more than 60 years on.

However, it was only in the mid-1980s and early 90s that Global Macro hedge fund investors, George Soros and Julian Robertson captured the world's attention and brought the concept of "hedge funds" to the broader public. Both produced high double digit returns for three decades but came to spectacular ends during the collapse of the tech bubble in the late 90s (Jaeger & Pease, 2008).

And with the downfall of these well-known funds, the story of superior performance began to change within the hedge fund industry. Hedge funds were then and still are today, sold to investors on the argument of diversification due to their low correlation with traditional stocks and bonds type investments. The reasons for this are two-fold, firstly, hedge fund performance has since then, been well below what it was in the latter half of the twentieth century. And secondly, the twenty-first century is experiencing unprecedented low levels of interest which have attracted institutional investors, representing pension funds and insurers who are looking for more appropriate levels of risk related return (Kat & Palaro, 2006).

However, many characteristics of hedge funds such as the lack of transparency, illiquidity, often highly leveraged positions, and the typical two plus twenty incentive fee structure are extremely unappealing to these institutional investors, especially of the institutional variety. Consequently, there is great interest in hedge fund replication strategies that can clone hedge-fund-like returns while still maintaining a similar systematic risk profile (O'Doherty, Savin, & Tiwari, 2016). Not only are these strategies completely transparent but they are done so through liquid instruments such as listed shares and money markets. Additionally, their fee structures are a fraction of the hedge funds.

Many hedge funds, themselves, are beginning to evolve to account for their own shortcomings. Funds are joining investment “platforms” as opposed to going it alone in order to keep down overheads and improve compliance. Even the sacred “2-and-20” fees are getting pushed back, with the average management fee during 2015 at 1.63 percent and profit share at 17.9% (Wille & Waite, 2016).

1.3 Background to Factors & Replication

Factors can be defined as any characteristic relating to a group of securities. In the case of this research, JSE shares, which help to explain their return and risk. Research on this topic is not new and has been going on since the 1970s. It has, however, only become more widespread as an investment tool in recent years through indexation which has allowed for passive replication (Bender, Briand, Melas, & Subramanian, 2013).

Hedge funds are often regarded as having a very low correlation to traditional asset classes and often use a variety of financial mechanisms and strategies in order to deliver returns. Generally, each strategy is vastly different from one to the next (Fung & Hsieh, 2006). But if a linear relationship can be identified between a hedge fund's expected return and the risk premiums from appropriate factors, then a passive systematic portfolio can replicate that risk exposure and hence the return profile (Hasanhodzic & Lo, 2007).

The use of factor investing has already started to become mainstream and accepted as a viable alternative to actively managed hedge funds. These factors are being packaged into ETFs, no longer just a beta tracker but deemed as "smart beta". While most of these smart beta ETFs cannot go short, they are still able to reverse-engineer most hedge fund strategies and replicate much of their performance for a just a fraction of the cost (Wigglesworth, 2016).

With these ETFs conveniently packaged and combined with the recent poor performance of actively managed funds, they had seen a $45bn inflow with a contrasting net $77bn outflow of hedge funds for the first ten months of 2016 (Wigglesworth, 2016)

1.4 Research Objectives

The purpose of this research paper is not to make a determination whether hedge fund replication is a better investment tool than hedge funds themselves. It is, however, to prove which factor styles are relevant to South African hedge fund performance, their optimal weightings when trying to replicate performance of South African hedge funds, and to minimise the tracking error in the replication.

More explicitly, the aim is to design a trading strategy that allows for the mechanical and passive trading of cash, stocks and bonds. To generate returns that are comparative to hedge funds or at least mirror the performance of the industry indices.

Chapter 2 – Literature Review

2.1 Introduction

Before this research can even begin to discover what the optimal mix of style factors should be in order to replicate hedge fund performance, there are a number of key areas in which the literature and theory should be explored further:

1. What makes it possible for hedge funds to be replicated?
    - Alpha, traditional beta and alternative beta
2. Why should investors choose replicated funds over their traditional form?
    - Liquidity, transparency, fee structure and manager specific risk
3. What sort of regulation applies to hedge funds and replication?
    - Dodd-Frank Act and CISCA
4. Which method of replication has been chosen for this research and why?
    - Factor models vs payoff distribution
5. Which styles should be considered in the replication method
    - Equity based styles
6. What should the replicated fund be benchmarked against?
    - Indices & bias
7. How does one determine the optimal mix of risk versus return in hedge funds?
    - Portfolio Theory

2.2 Alpha, traditional beta and alternative beta

Historically, returns from hedge funds were touted as being superior against all other asset classes, especially from within the industry itself. Although, the performances of hedge funds are now well below their prior levels, application of traditional performance measures such as the Sharpe ratio would generally indicate this to be true. However, hedge funds derive their exposure from unusual risk factors which makes traditional measures unsuitable. Thus these unaccounted for risk factors will get treated as alpha, suggesting superior performance (Kat & Palaro, 2006).

There are many "alpha protagonists" who hold the view the hedge funds are solely down to the specific skills of the hedge fund managers and argue that all returns out of the industry are "absolute". However, most modern research empirically shows that this is not the case and hedge fund returns can be characterised as being a blend of both systematic beta risk exposure and "skill-based" alpha returns (Jaeger & Wagner, 2005; Kooli & Sharma, 2012).

In the context of hedge funds, alpha is defined as the manager's expected return above the return attributable to their beta and that attributable to the risk-free rate. In general terms, its often aligned with the "skill" of the manager. It is the excess return they would earn by performing better than the average fund (C. Asness, 2004). Since this would clearly be very difficult to measure on its own, Alpha can also be viewed as the risk which cannot be explained by exposure to systematic risk factors and thus is measure of manager skill (Jaeger & Wagner, 2005; Kooli & Sharma, 2012).

While traditional beta is generated as part of the returns from long-only investments, hedge funds obtain their returns through non-conventional techniques such as short selling, leverage, and the use of derivatives. The resulting returns are deemed to be from alternative beta since there are fewer investors allowed to employ them than the traditional "buy and hold" investors (Jaeger & Pease, 2008).

In summary, if a return is only available to a select group of investors, the extraction of which is not a systematic process, then the return is due to true alpha. However, if it can be specified in a systematic way, but involved what has been described as "nonconventional techniques" above, then it is defined as alternative beta (Jaeger & Wagner, 2005). In the hedge fund industry, alternative beta is often repackaged and sold as alpha – simply "beta in alpha clothing" (Kooli & Sharma, 2012).

In contrast, the heavy performance-based compensation system within hedge funds creates a strong incentive for the generation of alpha by fund managers (Jorion & Schwarz, 2014). In fact, an increase to the incentive fee has shown a correlating increase to both the skewness and kurtosis of the distribution of hedge fund returns (Baker, Chkir, Saadi, & Zhong, 2017). However, with the pulling back of these fees in recent years, logic dictates a reduction in the generated alpha will follow.

And while there are no models which are able to replicate a manager's alpha, returns derived from risk premia (beta – alternative or traditional) can be modelled and thus replicated. Thus the aim of this research is to construct a factor-based model which aims to replicate the alternative risk profile of a hedge fund and thus mirror its corresponding returns.

2.3 Liquidity, transparency, fee structure and manager specific risk

The concept of hedge fund replication is very popular in both academia and the financial community. If offers an interesting alternative to investors to access the traditionally secretive hedge fund industry. But if clones can't offer a tangible, pervasive reason why they should be chosen over the funds themselves then they will be relegated to being a theoretical or benchmarking exercise (Chen & Tindall, 2014).

There are, in fact, many reasons why replicated funds are more attractive over their original incarnations. Most literature around replication at least touches on each of these points:

2.3.1 Fee Structure

One of the most well known facts surrounding the hedge fund industry is the excessive fees of "2 plus 20" which means an annual flat 2% management fee as well as 20% of profits over the hurdle rate. Fund of funds even charge an additional "1 plus 10" over and above this. If hedge funds are now largely composed of alternative beta returns then why do they still charge alpha level fees? Fees for investing in a replicated fund are negligible beyond the usual OTC fees (Fischer et al., 2016; Kat & Palaro, 2005).

2.3.2 Liquidity

Most hedge funds typically have lock-in structures where new investors are tied in for a period of time, anything between 6 months and 5 years. And even once the lock-in period has expired, investors are required to give a minimum of 1 to 3 months' notice that they wish to divest their funds. Some funds are even known to carry an exit fee, which they justify through a need of having to "rebalance the portfolio". Replicated funds by their very nature are invested in extremely liquid assets such as shares, cash and the bond market. Entering or exiting any of these markets is extremely efficient and investments are not tied up beyond the period they are required (Kat & Palaro, 2005).

Although high liquidity is generally seen as a positive for hedge fund replication, sometimes hedge funds may consciously choose to bear a liquidity risk as this would attract an accompanying premium return. Thus, excluding illiquidity is not always a given since the fund is forgoing beta (Fischer et al., 2016).

2.3.3 Transparency

Traditionally many hedge funds have operated as quintessential black boxes shrouded in secrecy. In the past, most investors were private wealthy individuals who were content in their ignorance as long as funds kept producing amazing returns.

However, today, the environment is quite different. Institutional investors have strict investment mandates due to regulatory standards. Although improved, hedge fund investors still struggle to accurately assess the risk-return characteristics of funds (Kat & Palaro, 2005).

Replicated hedge funds are fairly transparent and any investor should know exactly what type of risk premia they are being exposed to. The only concern is for the type of replication technique or method used by the clone. Some replicated funds use sophisticated mathematical models and this created complexity has a similar effect to lacking transparency, since many investors cannot understand the model (Fischer et al., 2016).

2.3.4 Manager specific-risk

Hedge fund managers may not always follow their promised or advertised investment style or strategy. This can cause a significant change in the fund's overall risk-return profile. In turn, this can negatively impact on the investor's own risk profile but without their knowledge. This style drift can arise from a change in investment philosophy, a gut-feel or even possibly from the manager having an "off" day (Kat & Palaro, 2005).

Replicated funds due to their systematic nature will never suffer from such risk, a risk which sees no corresponding return for the hedge funds.

2.3.5 Due diligence

Again related to the generally secretive nature of hedge funds, investors are required to devote a significant amount of time and money into researching hedge funds. Although third parties do provide such services, these do come at cost (Kat & Palaro, 2005). Replicated funds by their very nature are open and public.

2.4 Regulation

The Dodd-Frank act in the USA, in 2010, put more onerous reporting on hedge funds and their manager. The replicated funds are not under any such restrictions. Additionally, they can also be used to as tool for assessing systematic risk within the actual hedge funds (Chen & Tindall, 2014). “Regulatory access-at-a-distance” (Payne & Tresl, 2015), where authorities are better able to monitor what sort of systematic risks make hedge funds their returns without the managers having to divulge their proprietary strategies.

In South Africa, new legislation came into full effect from the 30th of October 2016 to regulate the operation of hedge funds in South Africa. They will now fall under the Collective Investment Scheme Control Act (CISCA), with the overriding aim to provide a legal framework within which hedge fund must operate (now technically collective investment schemes). CISCA refers specifically to how they may be advertised and marketed as well as to ensure investors receive complete and accurate information upon which to base their investment decisions (RSA, 2014).

South African hedge funds have reacted positively to the implementation of the regulation as it will help to shed the prior tainted image that the industry was only for “gun-slinging cowboys” (McClelland, 2016). It will also open up the industry to everyday retail investors which could potentially result in massive increase to inflows to the industry (KPMG, 2015).

2.5 Factor models, payoff distribution, and other techniques

It is currently accepted that there are two general methods of hedge fund replication. The most popular method is a factor-based approach and is regarded as being the most straightforward of the two.

2.5.1 Factor Models

This method involves selecting a variety of suitable and investable risk factors and arranging them into a portfolio (or weighting) composed of long and short positions so as to minimise the tracking error against the hedge fund index or individual fund that is being replicated. The portfolio with the smallest tracking errors and as such, the best “mimicking portfolio” created out of the in-sample analysis is then passively held for an out-of-sample period. This out-of-sample performance of the replicated fund can then be compared and contrasted against the target fund or index (Amenc, Géhin, Martellini, & Meyfredi, 2008; Kooli & Sharma, 2012).

This method of replication is often referred to as the "strict replication". The key issue regarding this method, is the selection of factors which have the same sensitivities of the target hedge fund that is being replicated. If the replication chooses appropriate factors that react to the market in the same way as the fund then the replicated portfolio will generate returns similar to those of the fund (Kat, 2007).

A large volume of research has been done in the area of factor models for hedge fund returns but these have mainly focused on ex-post, or after the event performance analysis. Fung and Hsieh (2002) were one of the first to popularise the use of asset-based style factors for fixed-income strategy funds using principal component analysis. They identified five generalised risk (style) factors which included Global Macro, Systematic Trend-Following, Systematic Opportunistic, Value, and Distressed Securities.

Agarwal and Naik (2004) used a multi-factor approach whereby they identified "buy and hold" risk factors such as equities, bonds and commodities indices, Fama and French "size" and "book to market" factors, a momentum factor, a credit risk factor as well as at-the-money and out-of-the-money S&P500 puts & calls.

Jaeger and Wagner (2005) were one of the few to have published about hedge fund factor models from an ex-ante, before the event, perspective. They took a multi-linear approach. Factor replication was not limited to equity styles and it was possible to imitate hedge fund exposures through liquid instruments, such as futures or forwards (Hasanhodzic & Lo, 2007).

Amenc, Géhin, Martellini and Meyfredi (2008) criticised the factor replicating approach, in that while this technique correctly tried to replicate the systematic risk inherent in the hedge funds through the selection of appropriate style factors, it often failed out-of-sample tests. They felt this was directly attributable to the difficulty in identifying the right factors to account for all the alternative beta risk. This criticism was shared by Kat and Palaro (2006), although they conceded that the technique worked better for portfolios of hedge funds, fund of funds and hedge fund indices since most of the individual risk was diversified away.

Jaeger and Wagner (2005) determined that while they could adequately model factor loads of hedge funds strategies when they were stationary, they believed that structural breaks in the systematic risk exposures could occur. However, their analysis of the data did not go on to test this. Amenc et al (2008) did identify that a sufficiently constructed factor-based model would need to account for the time-varying factor exposure of hedge fund returns rather than a simple regression which would only match the average past exposure and risk.

While the factor-based replication approach remains very attractive from a conceptual standpoint, it is still very much a work in progress and yet to be “solved”. The challenge lies in the difficulty of not only identifying the right factors but replicating the time- and state-dependent exposures of the hedge funds robustly (Amenc, Martellini, Meyfredi, & Ziemann, 2010).

2.5.2 Payoff distribution

While the factor-based model aimed to the replicate the month to month performance of hedge funds, the payoff distribution approach entailed matching the underlying statistical properties of a hedge fund’s returns. In contrast with the factor model approach, this method is a “loose replication” (Kat, 2007). Although this technique of replication was considered for the research and underlying principles were incorporated, this approach was not be covered in great detail.

This method, popularised by Amin and Kat (2003), was developed from the Payoff Distribution Pricing Model (Dybvig, 1988) and then further developed by Kat and Palaro (2006). Kat and Palaro (2005, 2006) argue that one invests in a hedge fund for the specific statistical return properties, not the absolute returns. And thus replicated hedge fund do not need to imitate the month to month returns of the hedge fund but rather generate returns that have similar statistical properties. As long as the generated returns displayed the needed characteristics, their sequence of arrival was of little importance.

Although a seemingly persuasive theory, there were some major flaws. While the methodology aimed at matching the moments and co-moments of the hedge fund, the main exception was the first moment (mean). Amenc et al (2008), Kooli and Sharma (2012) as well as Fischer et al (2016) found the mean returns of the replicating portfolio to be inferior to the index it was meant to replicate. This method was working well for long-horizon returns as it focused on merely matching the distributional properties of the hedge fund returns (moments and co-moments). However, it was unable to replicate their time-series properties which means it was a poor method of replication (Amenc et al., 2008).

Each of these above two approaches were completely different from the other and their degree of success was determined by how one defines the word "replication". If a replicated hedge fund created "equivalent" returns to an index or fund, the returns could have been almost equal in absolute terms or they could have been equal in distribution (Amenc et al., 2008). And this was typically the problem with such a statistical property matching technique. As Fischer et al (2016) agreed, investors were not interested waiting several years until they can acquire the sought after distributional properties, even if they were willing to overlook the differences in mean returns.

2.5.3 Alternative Techniques

Besides the two aforementioned approaches, there has also been much prior research on alternative approaches to hedge fund replication. This research paper did not go into these approaches in much depth.

Some of these included combining both the factor-based and pay-off distribution (moments-based) approaches into a combined method. This genetic algorithm, while providing encouraging results, only showed marginal improvement for a massive increase in complexity (Payne & Tresl, 2015).

Chen and Tindall (2014) compared "traditional" regression methods with what they referred to as parameter shrinkage or "non-traditional" methods. Their research also came to the conclusion of an improved technique, but at what cost? As already highlighted, a big attraction to hedge fund replication was its transparency and simplicity. By adding a level of complexity, replication may begin to mystify its investors, like hedge funds always have, as to their methods and workings. As well as potentially adding further costs onto the replication process.

O'Doherty, Savin and Tiwari (2016) proposed a combined approach where a diverse set of factor models were pooled, to have more accurately replicated a hedge fund index returns. Like many other articles, they concluded that the problem with the factor-based replication method was making sure an appropriate set of factors were identified in the first place. They noted that models with a large number of factors often suffer from overfitting and have poor out-of-sample performance. They tried to imply that rolling window monthly weighting adjustments would be excessively costly, however, these transaction costs were still a fraction of the 2-and-20 fees charged by hedge funds. And finally their research was based on the assumption that factor-based replication models always underperform their target indices. This research will address this through its selection of style factors and indices for analysis.

2.6 Selection of factor-styles

The established research on factor-styles is quite diverse but this research focused largely on the work done by Muller and Ward (2013) who looked at what effect picking Johannesburg Stock Exchange shares based purely on different style-based effects would have on the return of the portfolio.

Some of the seminal work done in this area in South Africa, was done by Van Rensburg and Robertson (2003) where they continued some of their prior work. They looked to examine three broad style clusters of “value” (earnings yield, dividend yield, price to NAV, prior five year’s earnings growth), “quality” (size, turnover, leverage, cash flow-to-debt) and “momentum”. Their univariate results did yield six candidate factors namely; price-to-NAV, dividend yield, price-to-earnings, cash flow-to-price, price-to-profit and size. However, their research resulted in a multifactor model, where only size and price-to-earnings yielded significance as explanatory variables.

In contrast to these results and many other studies, Muller and Ward (2013) found no evidence of the traditional small size effect. Their results even seemed to indicate severe underperformance by the smallest fifty companies (by market capitalisation) relative to the JSE. Another substantial result was the reaffirmation of momentum as an important style. This supported the findings of most other researchers such as Asness and Frazzini (2013) but is completely distinct from Van Rensburg and Robertson (2003) who found none of the measures of price momentum to be significant.

Of the twelve styles that Muller and Ward (2013) selected as a result of their literature review, they found the best multivariate style to be a combination of twelve-month momentum, return on capital, cash-flow to price and earnings yield. However, this study was not looking for the highest performing portfolio or hedge fund but trying to find optimal mix of these style factors which would best represent and mirror the returns of a hedge fund index. For this reason, all twelve of Muller and Ward’s original style factors were to be considered for the replication.

The research into the use of factors for investing purposes has been going for over 40 years and has not been resigned to exist only in academia or for theoretical purposes. Much of the business orientated research supports the traditional academic findings. They conclude that the best broad risk-premia factors include: Value, Low Size, Low Volatility, High Yield, Quality and Momentum (Bender et al., 2013). In fact, momentum and value have shown to yield significant return premia across all asset classes (C. Asness, Moskowitz, & Heje Pedersen, 2013).

A key element to consider when building a factor model is_ the cyclicality of the factor styles (Bender et al., 2013). While many factor styles will exhibit excessive risk-related returns over longer time periods, all of them will display substantial cyclicality over the short-term. Often this will include at least a two to three-year period of severe underperformance. Bender et al (2013) argued that this cyclicality is the reason why factor risk-premia have not been arbitraged away since most investors have shorter time horizons.

2.7 Hedge Fund Index

For the purposes of this research, the hedge fund replication was carried out against both the Hedge News Africa Long/Short Equity Index (HNALSI) and a sample of South African hedge funds.

Traditionally consideration was given to the fact that hedge funds have attracted investors not only on their promise to generate absolute or alpha returns, but also due to their low correlation to traditional assets. Consequently, the replication process would attempt to clone this low correlation as well (Fischer et al., 2016). Thus it would seem counter-intuitive that this research would choose to build a replication model based on traditional assets of shares and cash. However, initial research has suggested the long/short equity hedge funds, like the HNALSI already show high correlation to the JSE All Share Index so this should not be an issue when trying to replicate the index.

Any statistical research requires accurately measured data which is representative of the phenomena against which the research wishes to test a hypothesis. Hedge fund indices due to the very nature of the data collection process, present some potential biases. The research on biases presented by hedge fund indices is fairly overwhelming. Asness, Krail and Liew (2001); Jaeger and Wagner (2005) as well as Fung and Hsieh (2006) all reach similar conclusions regarding bias contained within indices, accounting for 3-4% of reported hedge fund outperformance:

2.7.1 Selection bias

Producers of hedge fund indices are reliant on the hedge fund managers to submit their data voluntarily and accurately. Since hedge funds are private entities, many thus refuse to release any propriety information or data to the indices. This creates a "self-selection bias" which can skew the index greatly. Additionally, the choice of whether to list the hedge fund in a database is also at the discretion of the fund manager. This means that it is difficult to assess whether all funds listed on such databases are truly representative of the universe of hedge funds (C. S. Asness, Krail, & Liew, 2001; Fung & Hsieh, 2006)

2.7.2 Survivorship bias

This is the result of hedge funds having failed to report their results, often due to poor performance and them ceasing to operate. Thus only successful hedge funds remain in the index, creating a positive bias (C. S. Asness et al., 2001). Fund and Hsieh (2006) argued that as the industry matures more and more hedge funds will stop reporting their results for other reasons, like successful funds that are closed to new investment. Ultimately they believe that much of this bias's impact will be mitigated or offset.

2.7.3 Backfilling (incubation) bias

Most new hedge funds have gone through a trial (or incubation) period establishing a strong track record before they are considered for inclusion onto an index. This history is then "backfilled" once the fund is included, again creating another positive bias (C. S. Asness et al., 2001; Jaeger & Wagner, 2005).

When considering the replication of the HNALSI, all of the above biases were taken into account in order to create a more accurate model. For this reason, the replication was performed on individual hedge funds as well, many of which form part of the index itself.

2.8 Portfolio Theory

Portfolio theory was developed by Harry M. Markowitz in the 1950s but its basic principles have held true today as it did then.

The current view of the day was that the current value of a share stock should be equal to the present value of its future dividend stream. However, since future dividends are uncertain, one can only calculate the expected present value of the discounted future dividends. But if investors were only concerned with maximising the expected values of their investments then they would construct portfolios with only one type of share stock. This share would be the one with the highest expected return (Markowitz, 1991).

Markowitz rejected such irrational investment behaviour. He concluded that investors are concerned with both risk and return and should be measured as a whole. He discovered that variance (and standard deviation) was the best measure for the risk of a portfolio. Using these basic principles, an investor was able to select a point from the set of Pareto optimal expected return, known today as the Efficient Frontier (Markowitz, 1991).

This should be no different for an investor deciding on which hedge fund to invest in, nor for the hedge fund manager choosing between shares and investments for their portfolio. In each case, they have not only chosen the investment with the highest net present value but have looked to create a portfolio which generates the highest present value, given an accepted level of risk.

2.9 Assumptions and Limitations of Theory

In order to have made this research achievable and construction of a replication model possible, certain assumptions or generalisations were made in order to facilitate the process. Some have been referred to in the literature and are summarised below:

2.9.1 Lack of alpha assumption

The basis of hedge fund replication is the ability to imitate the beta risk exposure of hedge funds. It is inherently not possible to replicate a manager's individual skill or alpha. This research was based on the premise that most current hedge funds do not produce any real alpha but it's returns were from alternative beta that have been mistaken for alpha (Kooli & Sharma, 2012)

Through most of the replication performed during the research there was a general degree of underperformance of the clones when compared to the actual hedge fund it was imitating. This was even more evident in the better performing funds. After the tracking error was considered, this underperformance was attributed to the non-replicable alpha or skill of the individual hedge fund manager (Jaeger & Wagner, 2005).

2.9.2 Transaction Costs

Some prior research maintains that the cost of creating and maintaining a factor-based replication portfolio would be prohibitively high (Kat, 2007). However, through the "style engine" the transaction costs of setting up and maintaining such a portfolio would be immaterial. Although such costs have not been given consideration in this research and thus no firm view point was taken, other than to exclude them from the replication.

2.9.3 Linear relationship

At its core, the style factor replication used in this research could be regarded as a linear multiple regression. This implied that the relationship between hedge fund returns and the style factors were linear which was not always the case and a fairly large assumption. Many hedge funds use highly dynamic trading strategies including the use of the more exotic trading mechanisms like derivatives. These would produce a non-linear, non-normal relationship (Kat, 2007).

This research has mitigated this possible weakness as much as possible by focusing on equity focused hedge funds. So although hedge fund performance is not generally correlated to traditional assets, the funds included the sample showed a strong linear relationship to the JSE (Fischer et al., 2016).

2.10 Summary of Literature Review

The main purpose of the literature review in this research was to delve into why the cloning of hedge funds was even potentially possible; provide reasons why investors would even begin to look at replication as an alternative to the original hedge funds themselves; and justify the selection of the method chosen for replication.

The replication of hedge funds is even possible because it is speculated that their returns in general are derived from what is deemed as "alternative beta". Very little of modern day hedge fund returns are extracted from individual manager skill or alpha (Jaeger & Pease, 2008; Kooli & Sharma, 2012).

Clones have been shown to be cheaper, more liquid, transparent in their structures and have less exposure to human risk since their operation is passive and systematic (Kat & Palaro, 2005).

By choosing replication, hedge fund managers could circumvent a lot of the new legislation that has sprung up in recent years to regulate the previously very lightly regulated industry. Additionally, replication can serve as a valuable tool for regulator to assess systematic risk as well as "regulatory access-at-a-distance" (Chen & Tindall, 2014; Payne & Tresl, 2015).

One of the main purposes of hedge fund replication and of this research was to demystify and simplify hedge funds as an investment. The method selected could not be overly complex or difficult. Additionally, most investors are looking for returns in the immediate term and are not prepared to wait a decade to see their investment generate the required returns (Fischer et al., 2016). For these reasons, factor styles were preferred over a payoff distribution type approach.

Appropriate factor styles need to be selected in order to correctly imitate the systematic risk from which the hedge fund extracts return (Amenc et al., 2008). The broad style factors considered were Value, Low Size, Low Volatility, High Yield, Quality and Momentum (Bender et al., 2013; Muller & Ward, 2013).

Indices are often regarded as better replication targets since the individualistic risk has been diversified out. However, indices suffer from some inherent bias – selection, survivorship, and backfilling (Fung & Hsieh, 2006). For this reason, both an index and individual funds were chosen for the replication sample.

Hedge funds within South Africa have a sizable spread in terms of accumulated returns and risk. Portfolio theory (Markowitz, 1991) was used a basis for the creation of an efficient frontier curve in order to optimise the level or risk and return equity hedge funds within South Africa should be targeting.

Chapter 3 – Research Questions

3.1 Main Research Question

The main research question identified through the review of the literature which was supported by the theory, was as follows:

- Can the returns of hedge funds in South Africa be replicated through long only investing in the equity market?

This research attempted to replicate or mirror the performance of the hedge funds selected for the sample as closely as possible, it did not attempt to outperform any particular fund or benchmark.

3.2 Supporting Research Questions

In order to answer the main research question, particular supporting research questions have been identified and will need to be addressed. Additionally, in seeking these answers, additional questions were raised. These supporting questions include:

a) Which style factors are representative of the systematic risk contained within the different hedge funds and index?
b) How closely do the optimal models replicate the performance of hedge funds and index in-sample?
c) How closely do the optimal models replicate the performance of the hedge funds and index out-of-sample?
d) What is the optimal level of risk versus return that hedge funds in South Africa should look to seek?

Chapter 4 – Research Methodology & Design

4.1 Introduction to the Research

This research was based on work done by Muller and Ward (2013) and with their permission, the use of their "style engine" to perform all the analysis. Their original research looked to find which factor styles produced the most significant and excess returns. However, this research looked to use these adjusted factor styles as a means to understand the nature of hedge fund returns and ultimately replicate their performance.

The inner workings of the Muller and Ward (2013) "style engine" are described in more detail within their research. Only a brief overview of its functionality was covered in this research.

4.2 Universe, Population, Unit of Analysis and Sampling

The universe for this research consisted of all hedge funds globally. While the population consisted of all the equity hedge funds within South Africa. Although the researcher has an idea of the identity of many of the hedge fund managers, there is no comprehensive list of the entire population and no sampling frame (Saunders & Lewis, 2014).

The unit of analysis, as in who or what should be providing the data, was the individual hedge funds. Although the actual data used in this study was aggregated through an index as well as individually for each hedge fund.

The sampling technique used for the research was non-probability quota sampling. This method is characterised as a technique which ensures that the selected sample represents certain features which the researcher has defined for their research population (Saunders & Lewis, 2014). For this research, it allowed for the selection of hedge funds and index with the following characteristics:

- Each fund and the index must have had at least 3 years of complete and accurate data which was also accessible and usable. Newer funds with less history cannot provide meaningful analysis.

- As already established through the literature review, funds were selected on the basis that the research would apply appropriate style factors that were able to replicate their systematic risk exposure (Amenc et al., 2008; Kat & Palaro, 2006). Since the Muller and Ward (2013) style engine is based on the JSE, selected funds were restricted to being either long/short equity or market neutral. In other words, made up of equity stocks.

- For similar reasons, only rand denominated funds were selected. Although no established research has shown a difference in style influences based on geography, the researcher used this selection criterion to control for any differences in systematic risk that could possibly occur.

4.3 Data Collection

The data collected for this research was from secondary sources which are publicly available. The data was quantitative in nature and collected as monthly returns, represented by a percentage of funds under management (Saunders & Lewis, 2014).

4.3.1 Hedge News Africa Long / Short Index (HNALSI)

The hedge fund index selected for the research was chosen with few alternatives. Anecdotal evidence, either from conversations with individual hedge funds or through the general media, pointed to Hedge News Africa as the independent go-to provider of hedge fund news in South Africa. They additionally produce a monthly index which is publicly available through their online portal (Hedge news africa.2016).

This data was made available as median monthly returns expressed as a percentage. As already establish, a long / short equity index was selected due to its closer correlation with traditional assets and its ease of replication.

The advantage of using a hedge fund index over individual hedge funds was highlighted by Kat and Palaro (2006) who pointed out that indices help diversify away individual risk which means one is left with just systematic risk or beta. Individual hedge fund returns will still contain that manager’s alpha which by its nature is not able to be replicated. As established in the literature review, this research aimed to only replicate the alternative beta or systematic risk of hedge funds.

However, upon interrogation of the HNALSI and confirmation provided by Hedge News Africa, it was found that the index contained much of the potential bias discussed in the literature review.

The hedge funds who provide data and make up the index were selected on a basis of whoever was willing to do so. This self-selection results in an index which generally only contains better performing funds and is not representative of the market. Additionally, Hedge News Africa admitted that funds fail to report their returns consistently from month to month, again skewing the true picture of the market, since they had to proxy the data.

Hedge News Africa further revealed that many funds also just stop reporting their results entirely. Some due to the fund failing and ceasing to exist and sometimes due to a fund becoming closed to new investors.

Ultimately this selection and survivorship biases result in an index which out performs the market (Fung & Hsieh, 2006; Jaeger & Wagner, 2005), thus not being truly representative of the market, only of the funds contained therein.

Further, the HNALSI used no weightings in its composition. This means that funds of one million rand were given the same consideration as hedge funds of over one billion rand. Without weightings smaller hedge funds could have significant influence over the movement of the index while only comprising an insignificant amount of funds under management. This would make the index a poor representation of the actual hedge fund market.

4.3.2 Individual Hedge Funds

Despite there being issues with the creation of the HNALSI and its mean returns, the hedge funds making up its composition are broadly considered to be representative of the industry. Thus these funds formed the starting point for the selection of funds in the sample. Since there are no complete databases or lists of all funds within the industry, further funds were added either through general information searches on the internet or through informal suggestions from various professionals in the market.

All of the funds added to the sample, fulfilled the previously mentioned criteria regarding sufficient history, having an equity focus and being denominated in Rand (and thus a South African focus).

Almost all hedge funds report their monthly returns via fund facts which are publicly available on their company websites. This data was extracted from these documents which the researcher used to create a database of monthly hedge fund returns. The hedge funds included in the research are listed in appendix 1.

4.4 Overall Research Design

The research consists of mainly longitudinal studies and through experimentation, studying the causal links between style factors and hedge fund returns (Saunders & Lewis, 2014).

4.4.1 Style Engine & Basic Replication

The “style engine” is a model built into MS Excel which uses VBA code to extract and manipulate data out of Access databases. The model creates a portfolio of shares from the JSE based on the particular selection of styles as well as the weighting assigned to each style. The balance of the portfolio can be tailored to include a portion of cash, bonds or other mainstream indices such as the All Share Index (J203). In their research, Muller and Ward (2013) were able to establish the best performing styles on the JSE since 1986 as well the best performing styles in combination. Best performing refers to the portfolios which yielded the highest cumulative returns over that period.

For this study, the process was essentially done in reverse. Using the HNALSI or any of the sample funds, the required cumulative returns which the research was attempting to replicate was a known quantity. The research tested various combinations of styles to see which combinations mirrored the performance of the HNALSI or hedge fund the closest. The relative weights of the styles, cash (in the money market) and the JSE All Share index (J203) was established through iterative calculations performed by the solver function within Excel which produced a result with the overall smallest tracking error.

4.4.2 Styles Data and Selection

The data for the styles was a combination of JSE share price and company financial statement data from the last 30 years. One of Muller and Ward's improvements over prior research was the improved data set which they had employed and over a much longer time period. In addition to this, they have made the necessary adjustments to account for possible problems in the data. Such irregularities include: dividend receipts, scrip dividends, company name changes, newly listed & delisted companies, and the unbundling of subsidiaries.

In compiling the style factors, the engine uses the top 160 companies which it divides into five equally weighted portfolios (quintiles), after ranking the shares in terms of which ever style is being applied (Muller & Ward, 2013).

The initial twelve factor styles taken into consideration for this research were drawn from Muller and Ward (2013), many of which were used in the final analysis. Each style is divided into quintiles and ranked based on its relative performance in that particular style.

Below is a summary of the systematic factors which were used in the replications and the ratios or measurements which were used to capture this risk (Bender et al., 2013):

a) Value

Implies shares that have a low market price relative to their fundamental value and earnings. This research captured it through **Earnings Yield**, **Dividend Yield** and **Cash Flow to Price** ratios. The best performing ratios were chosen for these measures (top quintile).

b) Quality

Shares of companies that are characterised by low debt, stable growth and other metrics which signify "quality". This has been captured through **Return on Equity** and **Interest Cover**. As per Muller and Ward (2013), the middle quintile was chosen for each of these measures.

c) Momentum

Shares which have shown strong recent past performance. The best **Momentum** measure suggested by Muller and Ward (2013) have a formation period of twelve months with a three month holding period.

d) Low Volatility

Shares with lower than average volatility, beta or idiosyncratic risk. Although not originally Muller and Ward (2013) styles, through the research, **Beta** and **Volatility** were found to be good styles for hedge fund investment. For each measure the fifth quintile was used, being shares with the lowest beta and lowest volatility.

e) Cyclicality

This is not a style in itself, however, due to resources dominating South Africa's JSE, the researcher felt that the contrast between **Resource** and **Non-Resource** stocks should be reflected in the replication of fund performance. Muller and Ward (2013) also identified the effect that the commodity cycle has on returns and although not a persistent style, these styles have had a significant influence over specific time periods.

f) Co-moments

Although not a traditional factor style either, borrowing from the payoff-distribution model, the researcher found the co-moment of **Skewness** to help in the replication of the funds and index for specific time periods. Skewness alone would not be able to imitate the month to month returns, but it would assist in generating returns that had similar properties to a hedge fund or index (Amenc et al., 2008; Kat & Palaro, 2006).

g) Money Markets and JSE All Share Index

These variables are part of the hedge fund replications, but are not particular investment styles. They are easily tradable and simple market mechanisms available to fund managers. The money market consists of highly liquid financial instruments that have short maturity dates which are used for short term borrowing and lending. Currently these return rates vary between 7 and 7.5% (FundsData Online, 2017). Over 60% of investment portfolios will carry more than 10% of their total funds under management in cash (Kennon, 2016). By using JSE All Share Index as a factor, one can capture the overall risk within the South African equity market.

The list of which factor styles were not used would be too numerous to discuss in detail. It is, however, worth noting that this research eschewed much of the popular literature by excluding the small size factor (Fama & French, 1992). The "style engine" uses the top 160 shares (by market capitalisation) on the JSE which encompasses over 98% of the market capitalisation. There is very little liquidity in many of the smaller cap shares and they would not be investable for a large hedge fund, let alone the replication. In addition, Muller and Ward (2013) found the size effects to be temporary at best and in some periods even showed underperformance for the very small companies.

4.4.3 Data Analysis

This research has taken a very different approach than other recent factor based replication studies (Fischer et al., 2016; O'Doherty et al., 2016; Payne & Tresl, 2015). And as such, the analysis of the data did not follow any established or prescribed methodology other than use of generalised techniques such as rolling windows and weightings. This was largely due to the use of the Muller and Ward (2013) "style engine" for the selection of factor styles rather than the use of listed indices as benchmarks.

Initially, once the monthly return data was captured into the database, each fund was compiled into a cumulative relative returns index showing the growth of the fund over its lifetime.

Several analyses were performed:

a) **Single Period Weighted Portfolio**

Each fund's relative accumulative returns for its entire history are then applied against the "style engine". An initial single period replication solution is found. This initial replication imitates the performance of each hedge fund through the use of a single fixed weight portfolio of style factors.

It must be noted that although the weighting of invested styles remains fixed for the entire replication, the underlying shares contained within each factor style changes and was rebalanced each month. This initial replication was not seen as a finished and accurate model but merely seen as an initial investigation into the type of styles that would be present within the hedge fund returns.

b) **Multi Period Weighted Portfolios – rolling windows**

A similar replication is carried out using three year rolling windows. For each date of the fund's lifespan, the preceding 36 months of returns are used to create a weighted portfolio of factors to replicate the fund's performance over the window.

For dates close to the start date of the fund, the windows were as large as the fund's age, running up to a maximum of 36 months.

These rolling window portfolios were then used in several ways:

i) Each monthly weighted portfolio that encompasses a particular return date (or data point) in each portfolio was averaged to a create new weighted style portfolio. Thus each new weighting contained 36 weightings, from the date of that particular portfolio of styles to the 35 multi period weighted portfolios which follow that date. The average (mean) weighted styles for each date were compiled into stacked area graphs showing the relative investment style changes over the lifespan of the hedge fund. The researcher deemed these graphs as the **Weighted Mean Styles**.

ii) As per the Weighted Mean Styles, the medians of the weighted styles for each date were also compiled into stacked area graphs in order to give a clearer picture of each fund's factor investment style by removing the less important styles. The researcher deemed these graphs as the **Weighted Median Styles**.

iii) The Weighted Mean Styles were used to imitate each fund's performance over its lifespan against its accumulative relative monthly returns. These relative monthly returns are generated by feeding the weighted mean styles back into the "style engine" for each month or data point. These replications were referred to as the **Goodness of Fit**.

c) Out-of-Sample Multi Period Weighted Portfolios

The Goodness of Fit replication was made retrospectively which would not be possible to emulate out-of-sample. In order to imitate each hedge fund's performance with any retrospective bias, full 36-month multi period weighted style portfolios were again created.

However, each date within the rolling window was weighted in order to give more recent style influences more influence on the overall style weightings. The nearest date being weighted at 95% as well as each previous period weighted similarly again on that period, until the furthest date in each 36-month rolling window being weighted roughly around 16%.

Each of these of weighted portfolios were then applied back into the "style engine" to generate one month of relative returns. Each month the replicated investment portfolio was rebalanced to the new style weightings.

d) Efficient Frontier

Most of the hedge funds included in the sample have vastly different inception dates. This made analysing the annualised returns and volatility of each fund ineffective since each funds risk exposure would be different due to their differing time periods. Consequently, the database was recompiled to generate annualised returns and volatility (standard deviation) for only the most recent three years. The data for each fund was then plotted against each other.

The efficient frontier (Markowitz, 1991) was then plotted. This was done by creating successive weighted portfolios of hedge funds with the lowest possible volatility at each percentage of annualised returns. The resulting curve represents the lowest possible risk (volatility) a hedge fund can achieve given a particular percentage return, all under the assumption that the fund is operating efficiently.

After making an assumption for a risk-free rate, a capital allocation line is then plotted from this risk-free rate point (a return that is achievable with almost no tangible risk or no volatility) to a tangent of the efficient frontier curve. Where they intersect can be regarded as the optimal portfolio.

4.4.4 Measurement and Presentation of Results

This research continued to follow Muller and Ward (2013) in its graphical approach of measuring and recording the results of the relative hedge fund returns. Correspondingly the research presented its replication results on a cumulative returns basis over the sample timeframe. This research also agreed that plotting and contrasting the results visually, aided in their interpretation far more readily than traditional methods. Such traditional methods entail the use of t-tests to look for significance on a monthly or quarterly basis. The researcher found these traditional methods to insufficiently portray the results clearly given the sheer volume of data.

The analyses presented in this research follow an experimental strategy of trying to establish causal links between variables (Saunders & Lewis, 2014), namely equity factor styles and hedge fund return distribution. However, in analysing the clones and establishing this relationship, the researcher deemed the use of ANOVA and the R-squared statistic extremely limiting and often misleading. This was another reason why the current research chose a graphical presentation of its results.

Again, similar to Muller and Ward (2013), many of the graphs contain a “price-relative” line comparing the clone’s performance with the original fund. This was created to show the relative monthly movements and was an easier means to assess the success of the replication visually.

4.5 Limitations of the Methodology

The researcher attempted to keep the methodology and processes for analysis as simple as possible. One of the reasons for distrust of hedge funds amongst general investors is the lack of transparency and convoluted means used to extract a risk premium. Any replication created using overly complicated models would be self-defeating as they too would only serve to confuse investors (Fischer et al., 2016). However, the researcher did identify potential weaknesses or limitations in addition to the ones identified as part of literature review. Some of these limitations may have potential to reduce the effectiveness of the replication to generate correlating returns to each fund or index.

4.5.1 Long only styles

The final replications were done using long-only equity styles. Some initial analysis done by the researcher that allowed the shorting of styles, showed signs of overfitting as suggested by some prior research (O'Doherty et al., 2016). This overfitting often leads to poor out-of-sample performance since the replication would only be imitating the hedge fund’s statistical properties and not its inherent investment strategy.

4.5.2 Limitation of styles

The research limited itself to only holding portfolios of shares on the JSE as per the relevant styles in order to create the replications. It did not use the multitude of financial instruments and mechanisms available to hedge funds such as derivatives, futures, options, convertible securities and the like. This increased the chance that the chosen style factors were not appropriate to account for all the alternative beta risk and hence replicate the hedge fund effectively (Amenc et al., 2008).

Additionally, the styles selected were “good styles”, meaning they are regarded as the best styles to maximise monthly returns. However, who is to say that many of the sample hedge funds selected don’t have poor fund managers who are following inefficient or ineffective investment styles. However, in order to replicate them sufficiently, the clone itself would have to use similarly ineffective factor styles. The research makes an assumption that fund managers are avoiding inefficient or ineffective styles.

4.5.3 Restricted history

During the collection of the sample of hedge funds, many of the funds found did not fulfil the criteria of having at least three years of monthly return data. Even of the funds that satisfied the minimum requirements, many of the funds had only been started within the last six years. This limited history and thus restricted number of data points, constrained the analysis of many of the individual funds. This ultimately resulted in less effective and less accurate replications.

4.6 Conclusion and Summary

This research employed a positivism research philosophy and through an experimental type strategy aimed to create generalised rules for hedge fund analysis and finally replication. The research took a clear deductive approach in that through a trial and error type basis, it tested for the optimal mix and weightings of different factors in the creation of a hedge fund replication model for each individual fund as well as an index. It was a quantitative explanatory study which used historical secondary market data that also consisted of a longitudinal study in order to create a model that fitted all the data both in-sample and out-of-sample.

Through the methodology of non-probability quota sampling, a selection of South African hedge funds was chosen that displayed the characteristics of having at least three years of data, were equity based and were denominated in Rands.

A total of 34 equity based hedge funds were selected for the sample along with a single index, the HNALSI.

The analysis employed the use of a "style engine" based on the work of Muller and Ward (2013). The basis for the factor styles chosen was based on research carried out by Bender et al. (2013) and included the broad styles of value, quality, momentum and low volatility. The measurements for these styles were refined through experimentation in order to establish causal links to hedge fund monthly returns.

The analysis produced both single and multi-period rolling window clones in-sample clones. These were used to provide an in-depth longitudinal study of each fund's evolving investment styles. Finally, an out-of-sample clone was attempted with varying degrees of success.

Chapter 5 – Results

5.1 Introduction

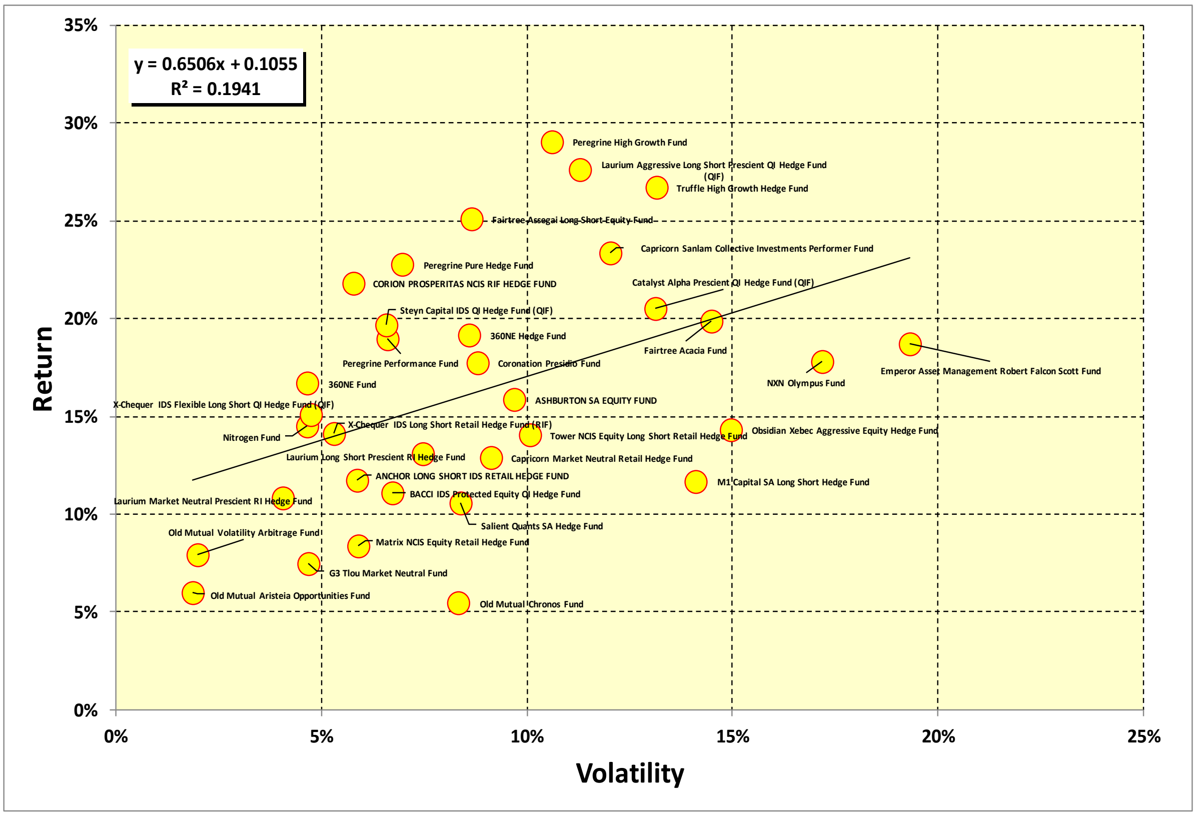
The results were acquired through the use of regression analysis, with use of the style engine to produce cloned accumulated return data as well as a longitudinal study of the changing factors which described the nature of these returns. The clones' performance was then compared and contrasted against their fund's historical performance.

The research results that follow are either grouped under each different analysis type that was carried out or by the fund the replication was cloning. Only the findings for each analysis were stated in this chapter. A detailed discussion regarding the results with their link to each research question were presented in chapter 6.

5.2 Annualised Returns and Volatility

Figure 1 details the annualised returns of all the hedge funds included in the sample, mapped against their volatility which is represented by the standard deviation of their monthly returns. The inception dates of the funds range between 1st January 2000 and 1st June 2013 with monthly returns up until 30th August 2016. A detailed list of these results is included in the appendix.

Figure 1: Annualised Returns vs Volatility of South African hedge funds



5.3 Descriptive Statistics on the Multi Period Weighted Portfolios

All the rolling windows were collated and some descriptive statistics were generated to get a better understanding of the effectiveness of the style factors used in the creation of the hedge fund clones. The results are presented in table 1.

It can be seen from the mean weighting of styles that momentum at almost 18% and low volatility at over 18% (Vol5 + Beta) are the generally the most influential. Surprisingly, an average of 39% of hedge fund returns in South Africa can be imitated by merely investing in the money market while the balance comprises of the rest of the factors.

As from the maximums, every factor style is hugely influential at some point during the replication of monthly returns. The medians show which factors are the most widely prevalent across all the funds. At 0%, this shows that the volatility styles are significant in less than half of all the replication periods, as were many of the other styles. Only the momentum style, at almost 8%, and investment in the money market (39%) appeared in over half of the rolling windows.

Table 1: Descriptive Statistics of entire sample's rolling windows

	Momentum12m1	VOL5	BetaOLS60m5	ROE3	InterestCover3	Skewness1	R	N	CashflowToPrice1	DividendYield1	EarningsYield1	STF3M	J203
Max	100.00%	94.42%	100.00%	95.40%	75.05%	66.34%	85.14%	60.10%	79.21%	100.00%	44.07%	100.00%	85.84%
StdDev	24.42%	19.94%	15.52%	8.62%	7.44%	8.75%	8.55%	4.02%	9.28%	13.35%	4.20%	29.64%	11.67%
Median	7.61%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	39.02%	0.00%
Mean	17.94%	12.01%	6.39%	2.43%	2.26%	3.63%	3.16%	0.58%	2.46%	4.20%	1.05%	38.96%	4.94%

5.4 Hedge Fund Replications

There were too many replications and results for all of them to be included. Consequently, the researcher has categorised the hedge fund results. They have been divided into replications that are a good fit with minimal tracking errors, replications that have a reasonable fit but possibly suffer from a systematic break and then funds which were replicated poorly or there was not enough data to create an accurate clone. Then a sample of these results, that best represent the effectiveness of the replication as well as which illustrate the pitfalls or weaknesses, were selected.

These breaks are when turbulence in the market results in the linear relationship between the style and systematic risk of the funds being disrupted (Jaeger & Wagner, 2005).

The selected results will be presented by fund, with the index and 5 additional funds chosen. The hedge funds were selected on the basis of including varying degrees of annualised performance and volatility, using figure 1 as a guide.

a) Peregrine High Growth Fund – highest annualised returns
b) 36ONE Hedge Fund – average annualised returns / average volatility
c) Coronation Presidio Fund – average annualised returns / average volatility
d) Old Mutual Volatility Arbitrage Fund – near lowest returns / near lowest volatility
e) Emperor Asset Management Robert Falcon Scott Fund – highest volatility

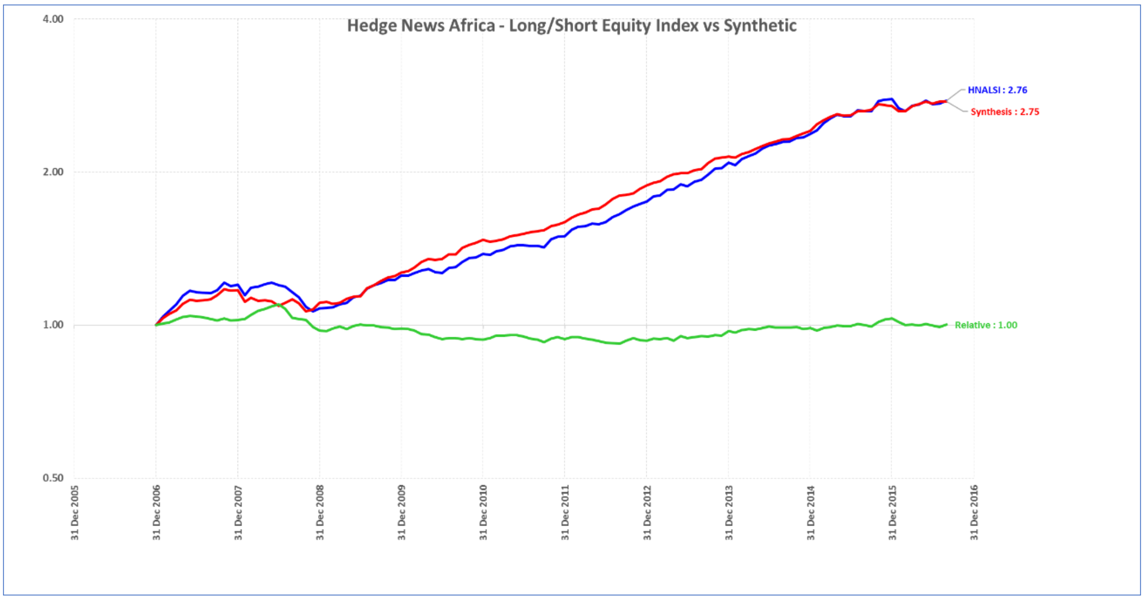
A summary of the effectiveness of the hedge funds were also included after the individual results.

5.4.1 HNALSI

Figure 2 shows the relative performance of the HNALSI tracked against its Single Period Weighted Portfolio clone. The index was created on the 1st of January 2007 and runs to the 31st of August 2016. The index's performance is imitated well over the entire period with only small systematic breaks. This is illustrated by the smooth and horizontal green relative line. Towards the middle of 2008, the relative difference jumps by about 10% before normalising and at the end of 2015 another small break occurs.

The single weighted portfolio consisted of roughly 45% in volatility styles and 55% in the money market (including rounding).

Figure 2: HNALSI Single Period Weighted Portfolio



0%	30%	15%	0%	0%	0%	0%	0%	0%	0%	0%	56%	0%
Momentum12m1	VOL5	BetaOLS60m5	ROE3	InterestCover3	Skewness1	R	N	CashflowToPrice1	DividendYield1	EarningsYield1	STF3M	J203

Figure 3 shows the Goodness of Fit replication for the HNALSI using the weighted rolling windows for the creation of the clone. This clone also starts from the inception date of the fund from the 1st of January 2007 running all the way to the 31st of July 2016. This replication is more accurate than the single period portfolio with the relative returns of the clone consistantly within 2% of the index. Although the relative green line does not appear overly smooth, it is comparatively level. The HNALSI clone shows a small break towards the end of 2014, similarly to what was seen in the Single Period Weighted Portfolio.

Figure 3: HNALSI Goodness of Fit

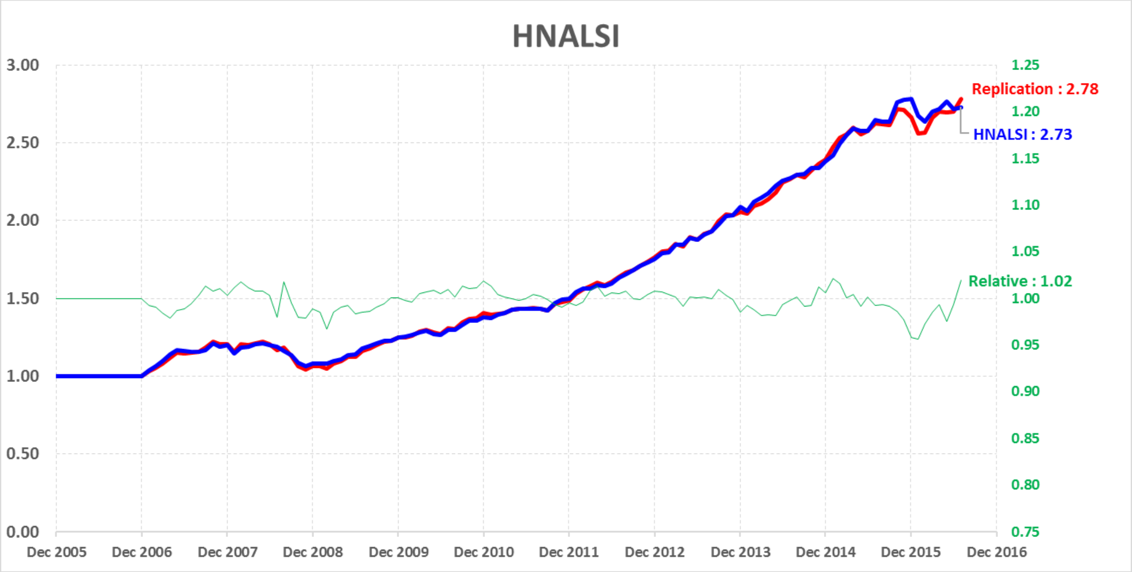


Figure 4 shows the Weighted Mean Styles of the HNALSI over the lifetime of the index. It is clear that investment in the money market has been a significant portion of the nature of the index's returns, just as it was for the Single Period Weighted Portfolio. Although, the importance of the other styles is perhaps not as clear. For this reason, the Weighted Median Styles were also created, as in Figure 5, to give a more definitive picture. Again, we can see cash (money market) as the most prevalent style. Skewness was fairly significant early on before giving way to momentum and ROE for certain periods. Beta (volatility) was a minor style for brief periods.

The significant and concerning observation from these graphs regarding the South African hedge fund industry is that over 50% of the beta risk and hence risk premium for the last ten years can be described through investing nothing more than in the money market.

Figure 4: HNALSI Weighted Mean Styles

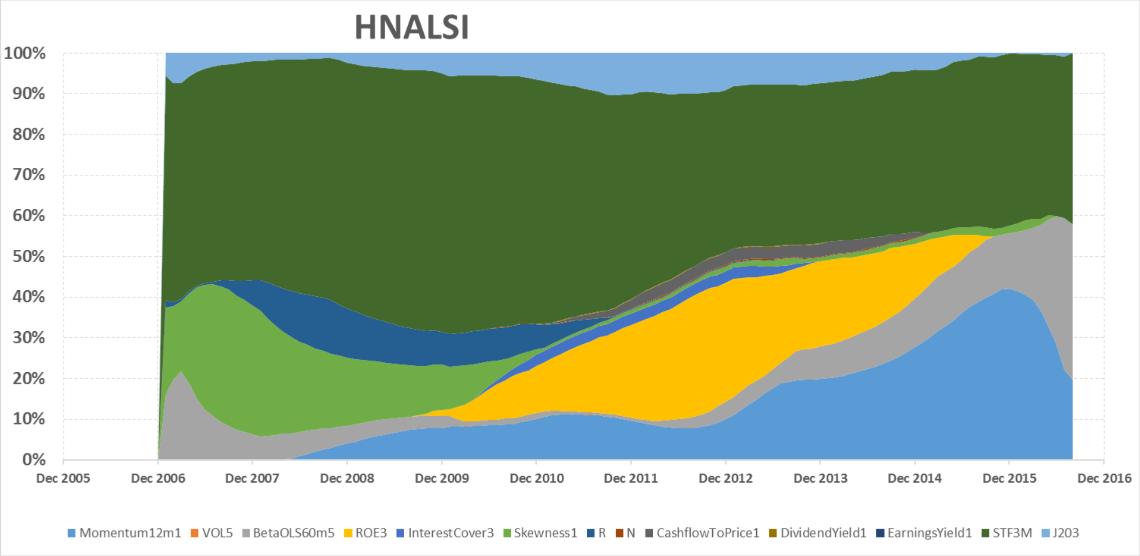


Figure 5: HNALSI Weighted Median Styles

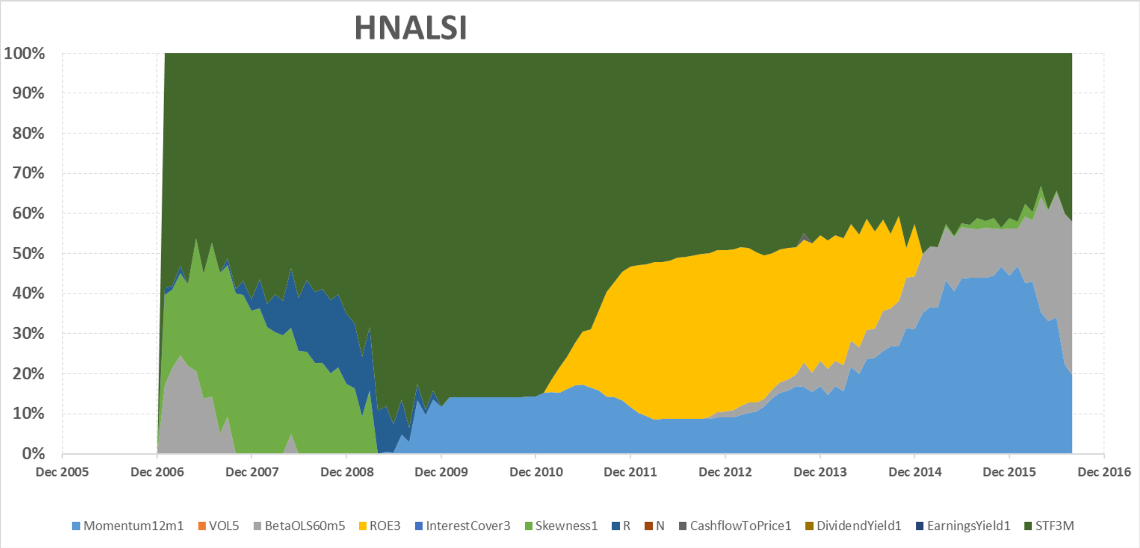
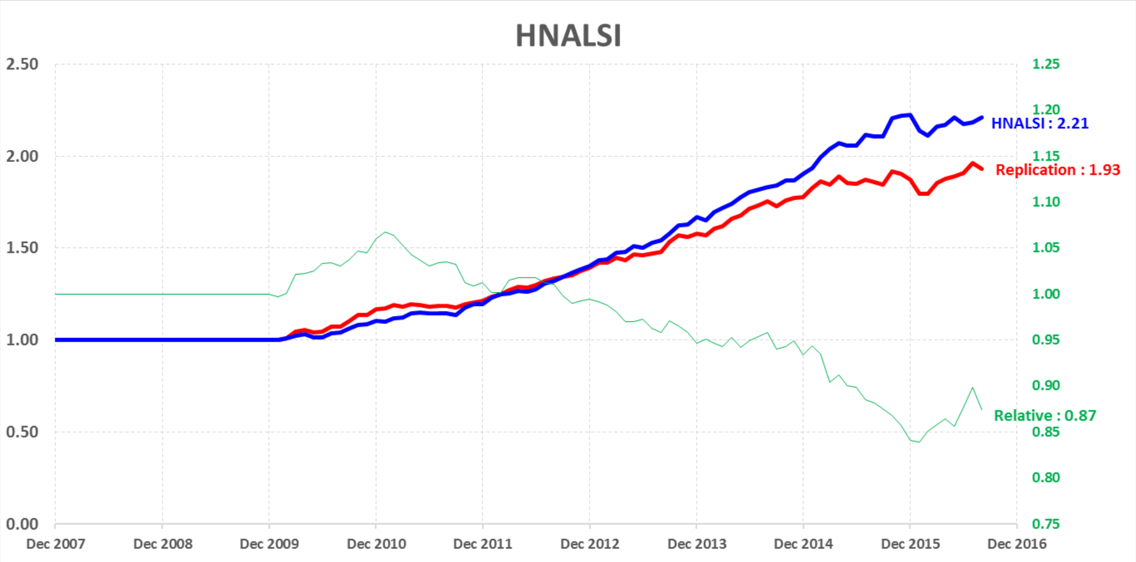


Figure 6 shows the Out-of-Sample Multi Period Weighted Portfolio replication results. This clone required a full 36 data points (months) before it could be implemented so this out-of-sample analysis only began from the 1st of January 2009. The clone tracked the HNALSI quite closely but did end up with significantly lower relative return. The moderate downward sloping green relative curve signifies a fairly consistent underperformance.

Figure 6: HNALSI Out-of-Sample Replication

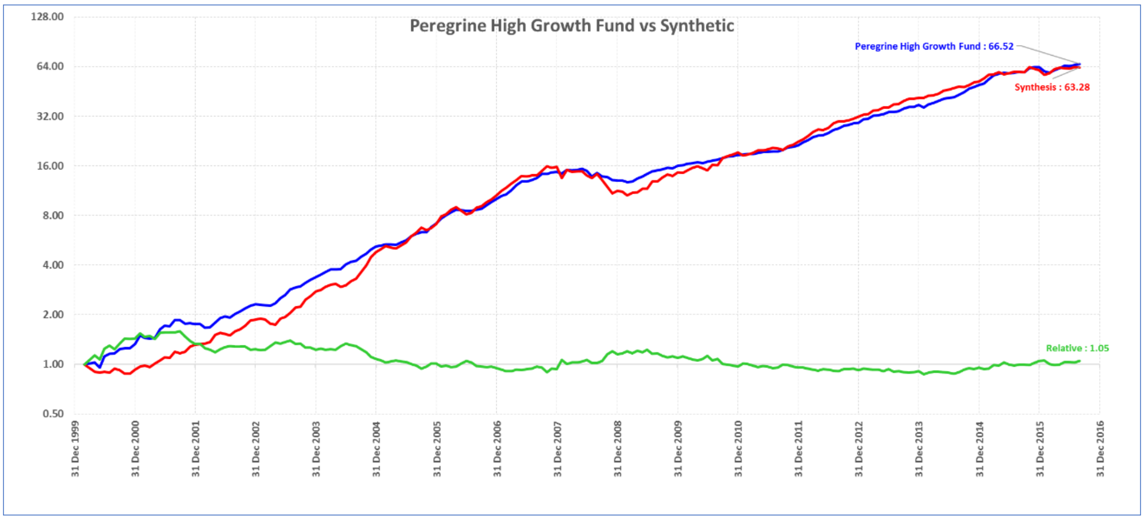


5.4.2 Peregrine High Growth Fund

The Peregrine High Growth Fund is one of the longest running and most successful in the history of South Africa's hedge fund industry. Figure 7 shows the performance of the fund since the 1st of February 2000 until the 31st of August 2016 where it has grown almost 67 fold. The Single Period Weighted Portfolio clone has imitated its overall performance fairly well, although it showed severe underperformance for the first three years, achieving close to parity on accumulative returns over its lifespan.

In contrast to the index, this fund showed a far more dynamic investment nature with 71% in momentum, 7% in volatility/beta and 22% in skewness styles.

Figure 7: Peregrine High Growth Fund Single Period Weighted Portfolio



71%	0%	7%	0%	0%	22%	0%	0%	0%	0%	0%	0%	0%
Momentum12m1	VOL5	BetaOLS60m5	ROE3	InterestCover3	Skewness1	R	N	CashflowToPrice1	DividendYield1	EarningsYield1	STF3M	J203

Figure 8 shows the Goodness of Fit replication for the Peregrine High Growth Fund. Again, this clone captured the returns of the fund well but with signs of steady underperformance until the end of 2014. For the last two years the replication's performance falls away completely as can been seen by the green relative curve.

Figure 8: Peregrine High Growth Fund Goodness of Fit

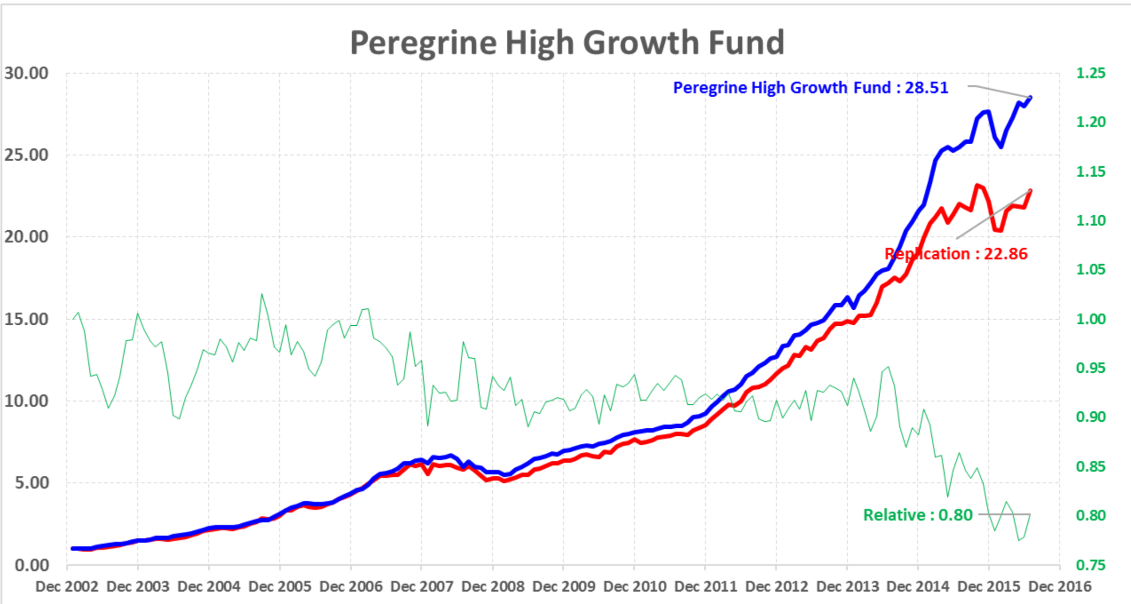


Figure 9 shows the Mean Weighted Styles of the Peregrine High Growth Fund. Momentum was a clear persistent factor style through the entire history of the fund. Although, when one looks to figure 10 showing the Median Weighted Styles, different periods of the fund's investment changing policy can be identified. The fund begins as a momentum / value (cash flow to price) style fund. After two years, the value positions get moved into resources before these all give way to a cash style with a much smaller momentum style position. This occurs around the global financial crises in 2007/2008. After 2010, the fund becomes a clear momentum and low volatility (beta/volatility) fund but by the end of 2013 it is shown to be predominately momentum.

After 2014, the weighted mean style shows momentum dramatically falling away. This is due an inherent weakness in the design of the rolling weighted windows. As the period moved closer to the current date, the clone has fewer and fewer data points in order to average. This means that the last few months have been replicated poorly which lead to the goodness of fit clone performing poorly over the last two years.

Figure 9: Peregrine High Growth Fund Mean Weighted Styles

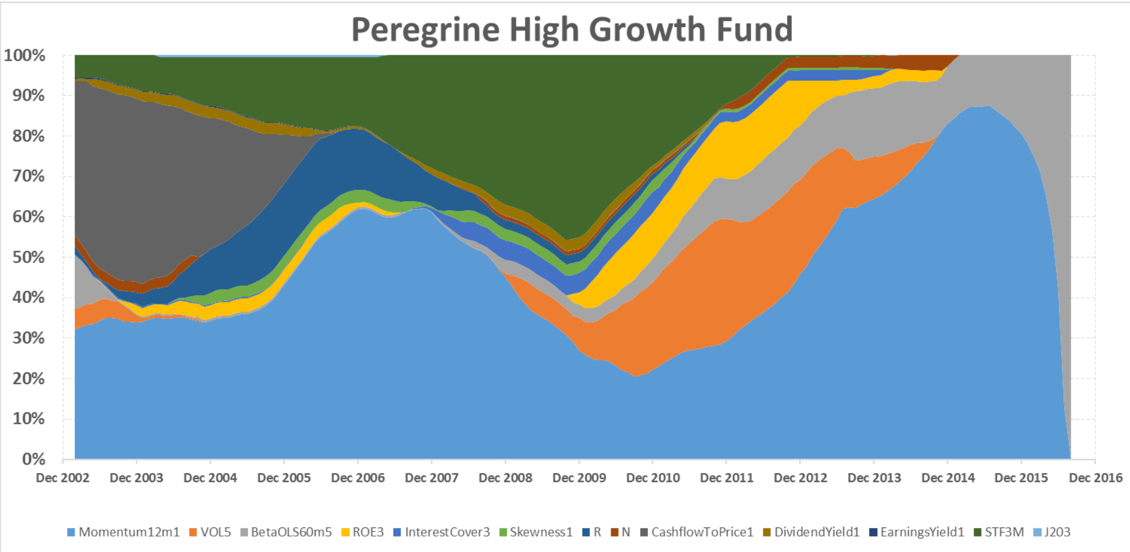


Figure 10: Peregrine High Growth Fund Median Weighted Styles

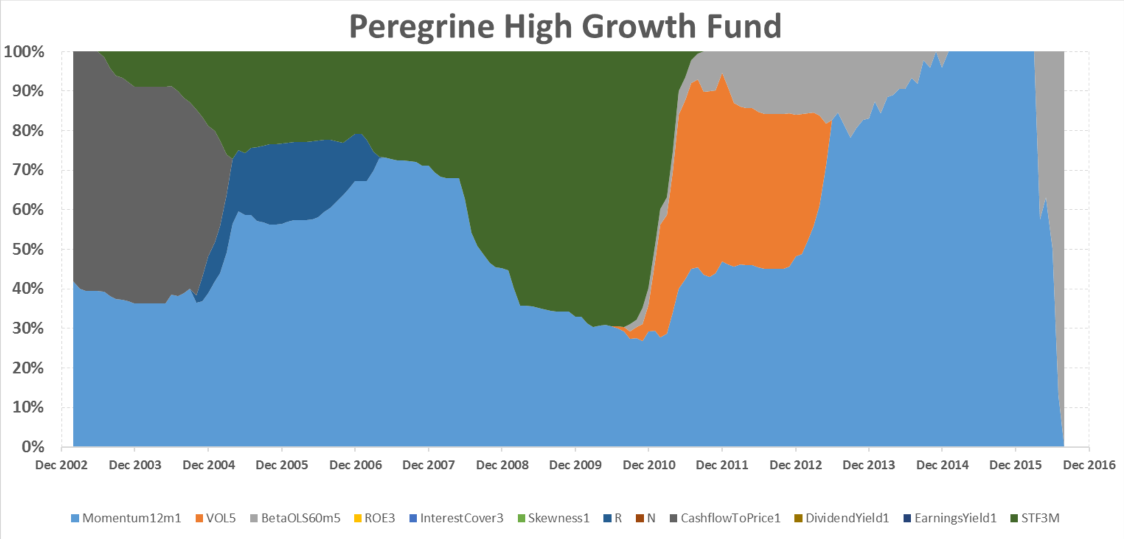
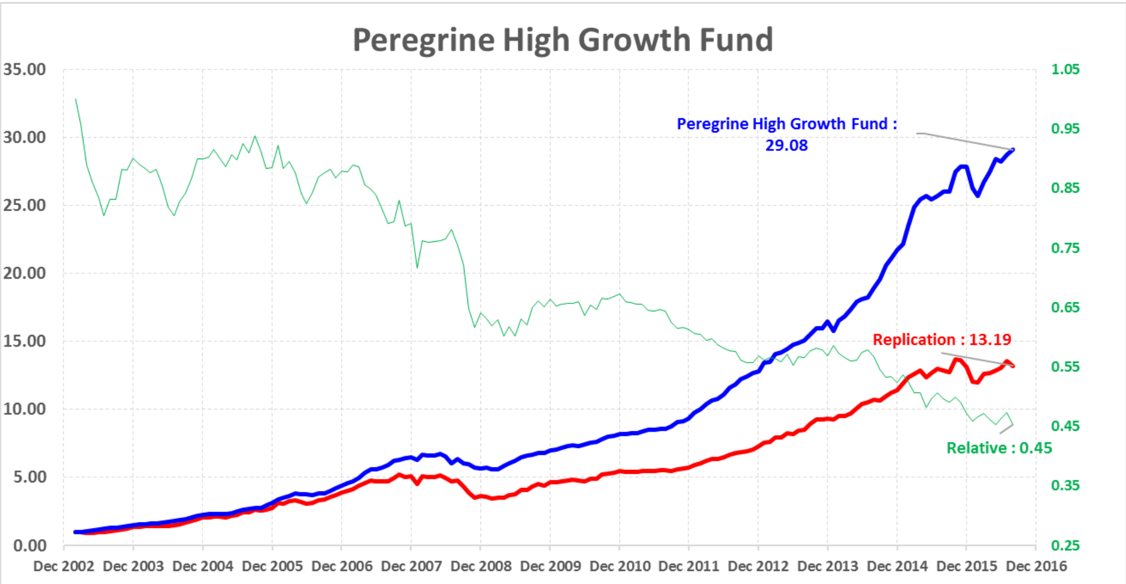


Figure 11 contrasts the Peregrine High Growth's fund performance against the Out-of-Sample clone. Unfortunately, the fund's monthly returns were poorly replicated which resulted in a severe underperformance over the 14 years. This underperformance was fairly consistent over all the periods with a significant systematic break around the global financial crises in 2008.

Figure 11: Peregrine High Growth Fund Out-of-Sample Replication

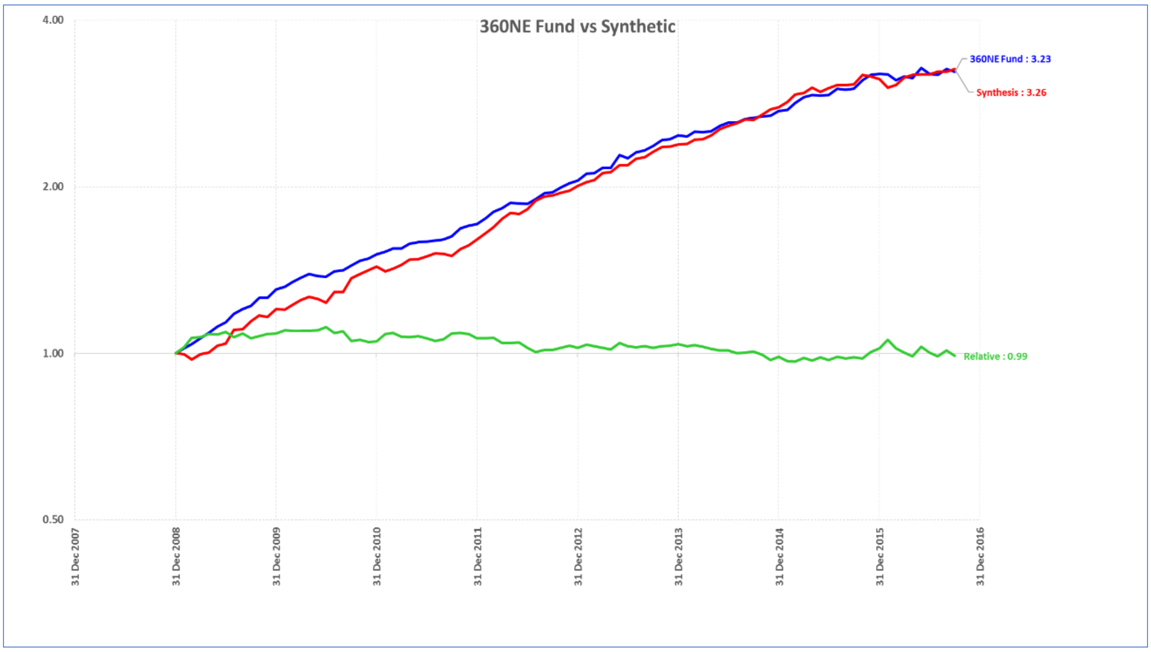


5.4.3 36ONE Fund

Figure 12 shows the relative performance of the 36ONE Fund compared its own Single Period Weighted Portfolio clone. The fund commenced on the 1st of January 2009 with returns up to the 30th of September 2016. This fund shows relatively small tracking errors but, again, shows small systematic breaks around the beginning of 2009 and right at the end of 2015 and beginning of 2016.

The single period weighted portfolio consists of around 47% in the money market but 44% in momentum styles and 7% in the co-moments style of skewness.

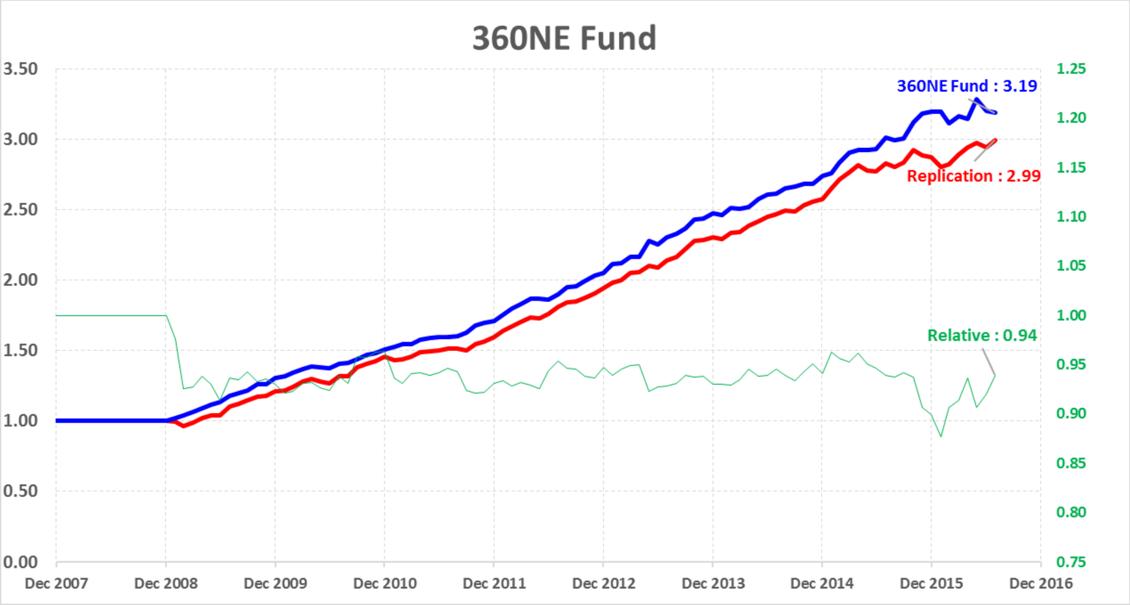
Figure 12: 36ONE Fund Single Period Weighted Portfolio



44%	0%	0%	0%	0%	9%	0%	0%	0%	0%	0%	47%	0%
Momentum12m1	VOL5	BetaOLS60m5	ROE3	InterestCover3	Skewness1	R	N	CashflowToPrice1	DividendYield1	EarningsYield1	STF3M	J203

Figure 13 shows the 36ONE Fund's Goodness of Fit replication. The clone imitates the hedge fund's curve extremely well except for two apparent systematic breaks. The first, as the fund started at the beginning of 2009, could either be due to volatile financial market post the 2008 financial crises or due to the clone not yet having enough data points to accurately describe the fund's factor style. Additionally, in December 2015, the replication seems to break down again, coinciding with a period of financial and political turbulence in South Africa (Hogg, 2016).

Figure 13: 36ONE Fund Goodness of Fit



Figures 14 and 15 show 36ONE Fund's Mean Weighted and Median Weighted Styles respectively. The fund's style can be broadly described as a 50/50 cash and low volatility fund. Just after the fund's inception it did have a period of momentum investing which has since given way.

Figure 14: 36ONE Fund Mean Weighted Styles

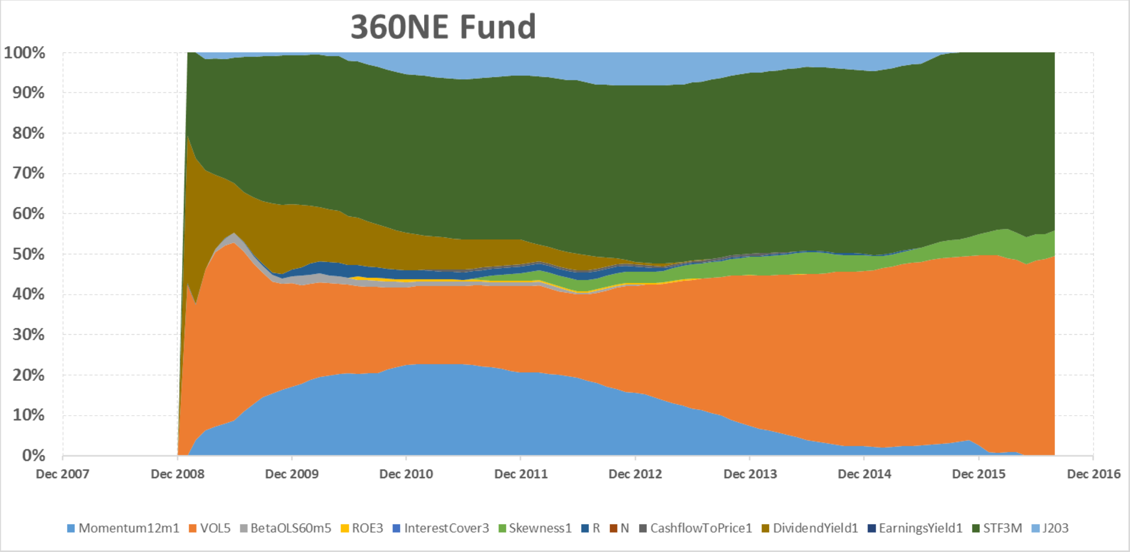


Figure 15: 36ONE Fund Median Weighted Styles

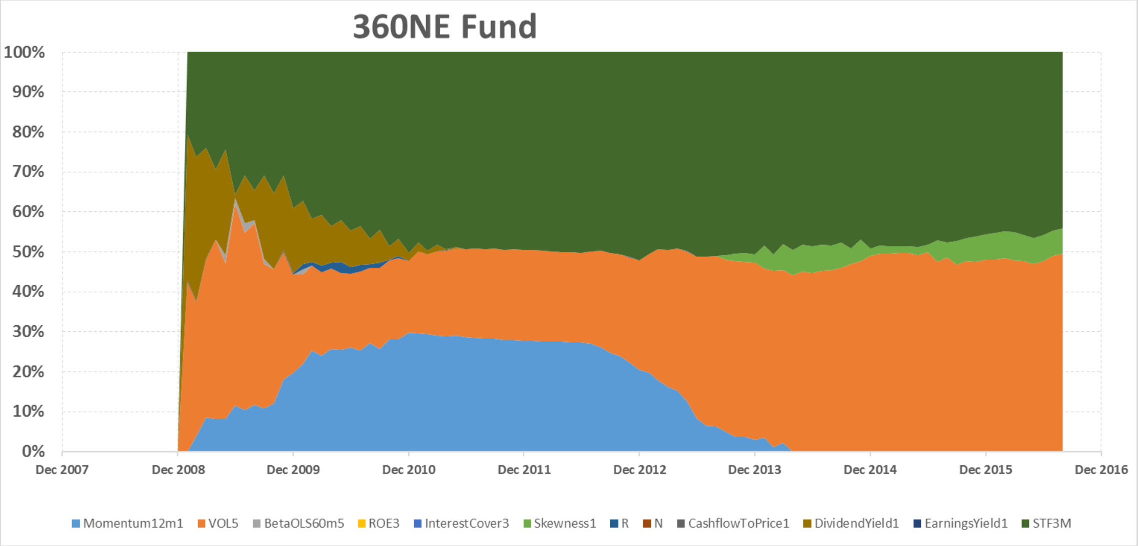
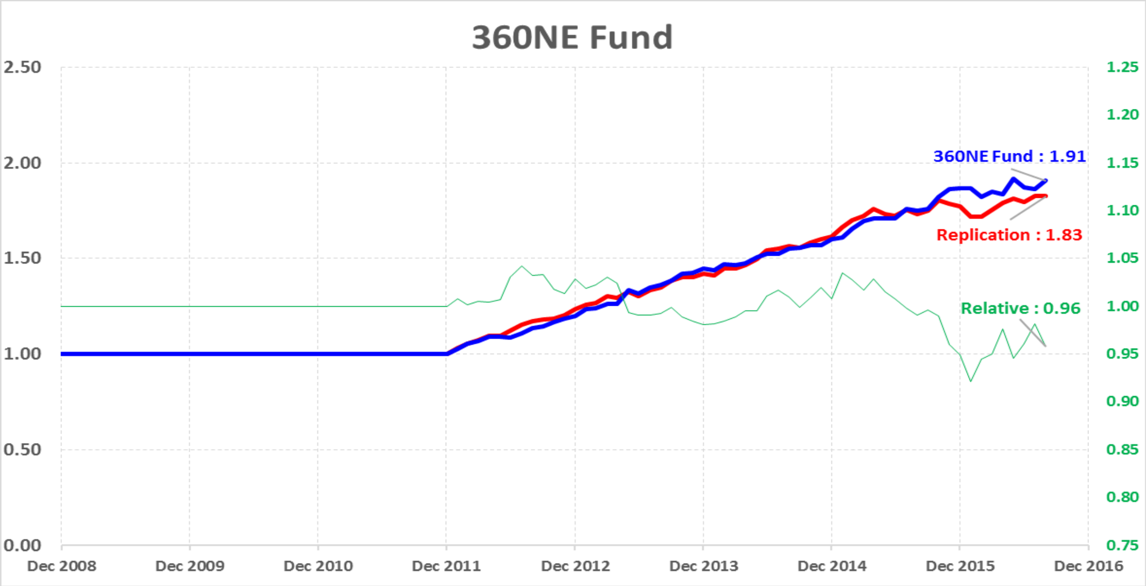


Figure 16 shows 36ONE fund's relative performance compared to its Out-of-Sample clone. Here the replication has performed very well as shown by the comparatively flat green relative curve. There appears to have been a breakdown of the clone in December 2016, again coinciding with the same systematic shock.

Figure 16: 36ONE Fund Out-of-Sample Replication



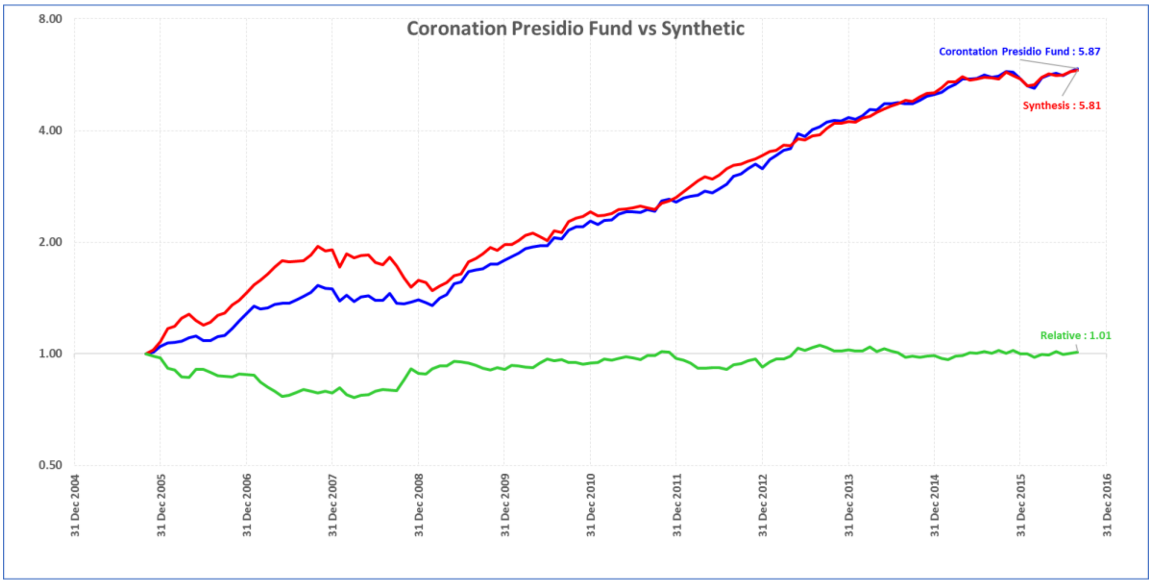
5.4.4 Coronation Presidio Fund

Figure 17 shows the Single Period Weighted Portfolio of the Coronation Presidio Fund from the 1st of November 2005 until the 31st of August 2016. The clone produces an overall accumulated return very similar to that of the fund. It also imitated the fund's monthly distribution well, as can be identified via the comparatively flat green relative curve. Between 2005 and 2008 the replication had a huge tracking error, as it actually far outperformed the fund with the tracking error reducing from 2009 onwards. This pattern was similar for many of the long running hedge funds. The Single Period Weighted Portfolio struggled to describe the earlier periods and experienced large tracking errors, with the accumulated returns then harmonising in later periods.

The Coronation Presidio Fund, as with many of the other funds, was negatively affected by the December 2016 financial losses but the clone seems to have imitated this downturn sufficiently.

For the single period weighted styles, cash is again greatly influential on the fund's returns at 23%. The factor styles consisted of Momentum at 35%, Return on Equity (Quality) at 34% and Skewness at 8%.

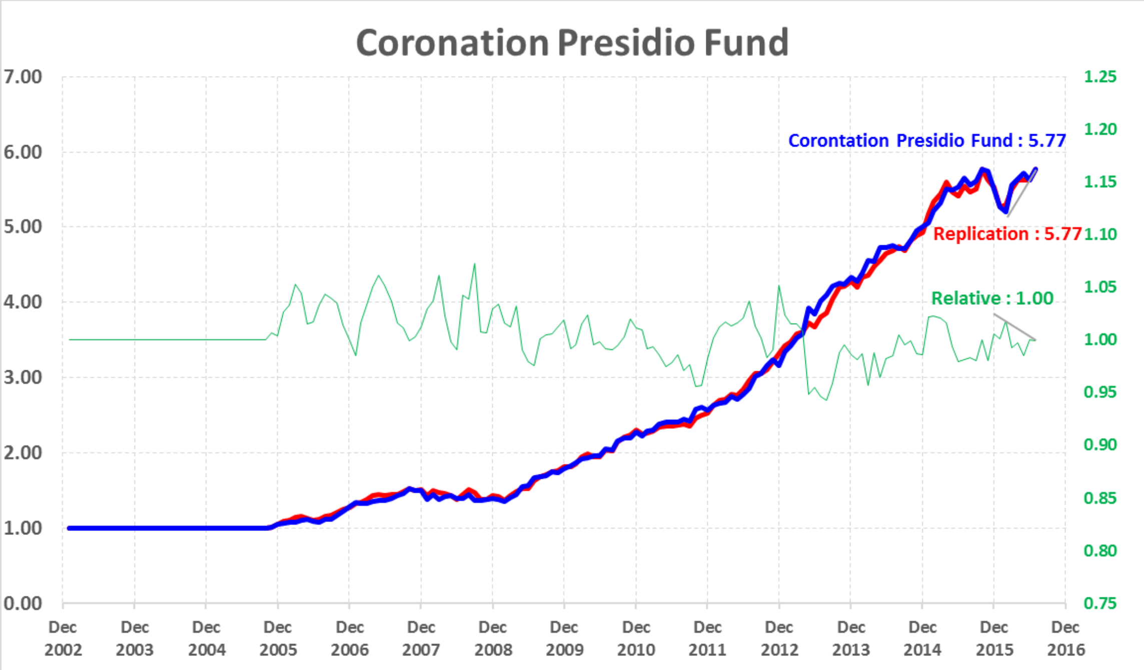
Figure 17: Coronation Presidio Fund Single Period Weighted Portfolio



35%	0%	0%	34%	0%	8%	0%	0%	0%	0%	0%	23%	0%
Momentum12m1	VOL5	BetaOLS60m5	ROE3	InterestCover3	Skewness1	R	N	CashflowToPrice1	DividendYield1	EarningsYield1	STF3M	J203

Figure 18 shows the Goodness of Fit clone which imitates the mean returns of the Coronation Presidio Fund well over its lifetime. The clone's accumulated returns remain within almost 5% of the fund over the entire 16 years.

Figure 18: Coronation Presidio Fund Goodness of Fit



The Mean Weighted Styles are shown in figure 19 but, as seen with the previous funds, the Median Weighted Styles give a clearer picture of the prevalent styles. In figure 20, the Coronation Presidio Fund began as a value (dividend yield) and cash fund. By the beginning of 2011 it had rapidly changed its investment strategy and adopted a pure low volatility style. By 2016, much of the low volatility had given way to momentum and cash.

Figure 19: Coronation Presidio Fund Mean Weighted Styles

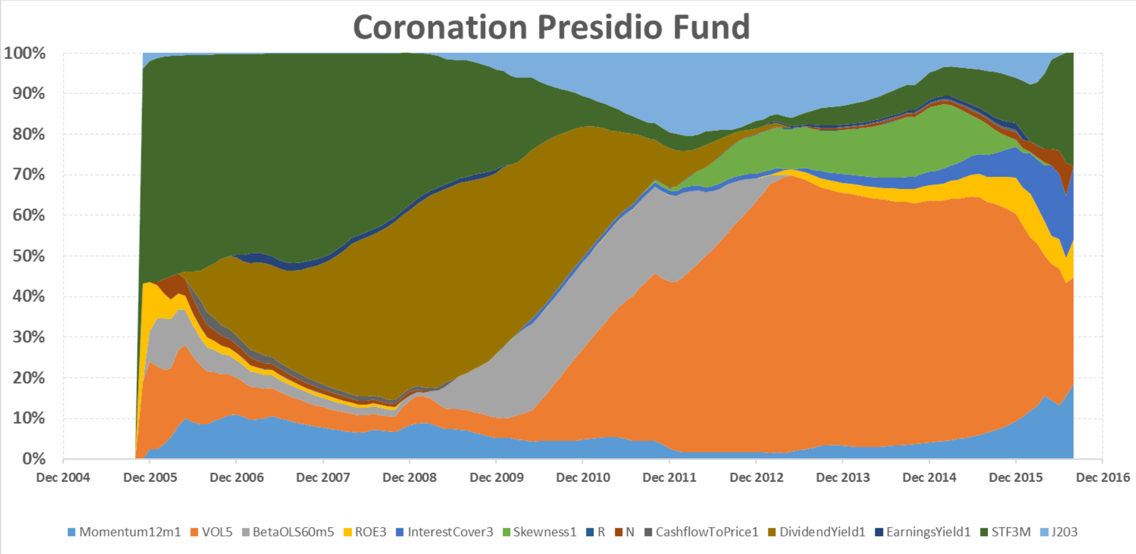
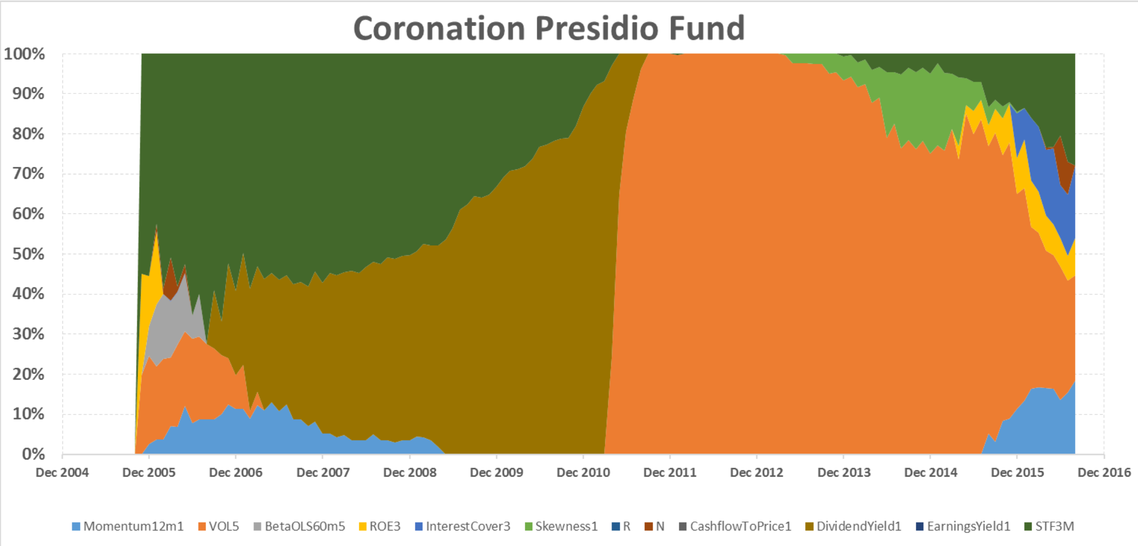
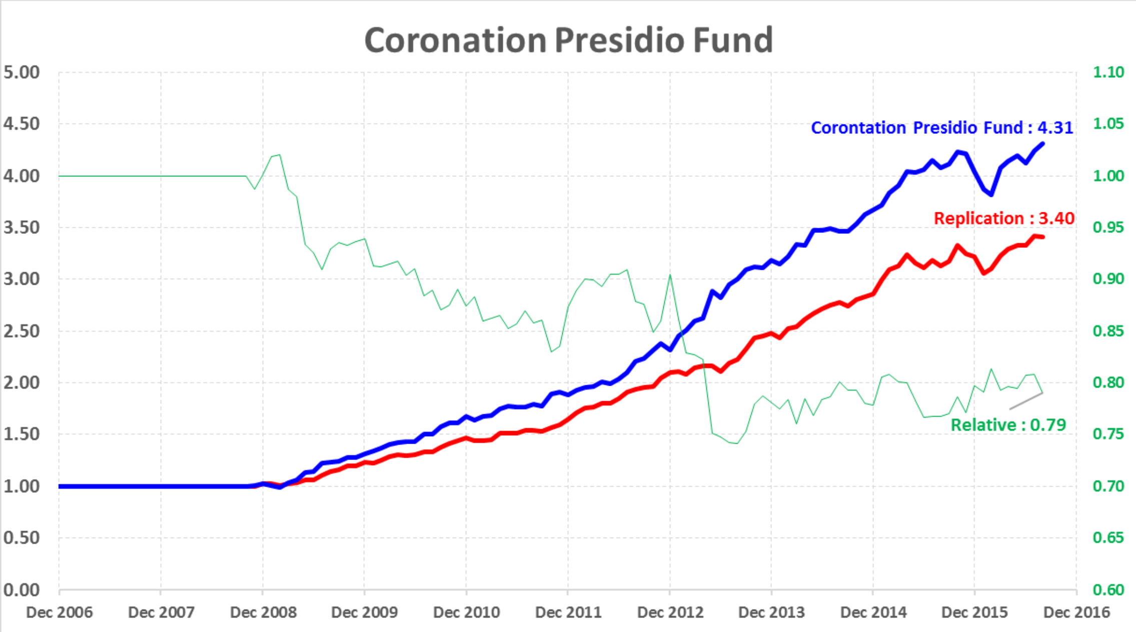


Figure 20: Coronation Presidio Fund Median Weighted Styles



Unfortunately, the Coronation Presidio Fund's Out-of-Sample clone performed quite poorly as can be seen in figure 21. The downward trending green relative curve shows a general consistent underperformance of its lifespan. But there were also two fairly large systematic breaks in the replication at the beginning of 2009 and the beginning of 2012. These most likely arose from Coronation's constant rapidly evolving strategy which the clone is unable to cope with due to reliance, although weighted, on 3 years of previous returns.

Figure 21: Coronation Presidio Fund Out-of-Sample Replication



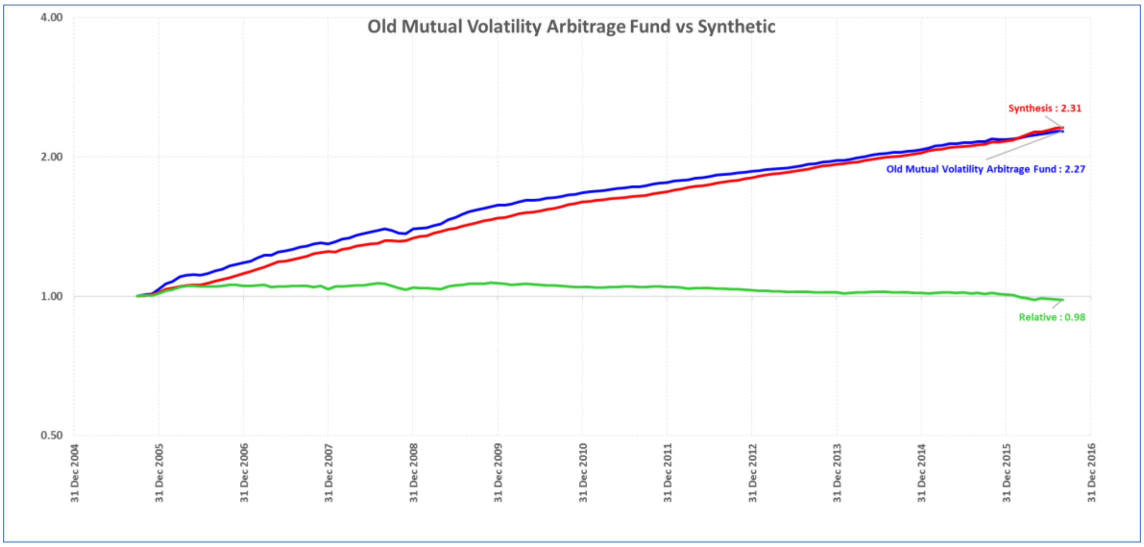
5.4.5 Old Mutual Volatility Arbitrage Fund

The net fund results displayed are from the Old Mutual Volatility Arbitrage Fund. As the Single Period Weighted Portfolio in figure 22 shows, the fund and consequently the clone, generated very low but consistent results from its inception on the 1st of October 2005 to the most recent results on the 31st of August 2016.

As already seen in figure 1, this low volatility in the clone was to be expected. And with such low volatility, even a Single Period Weighted Portfolio clone has generated a near perfect replication of the fund’s results.

The single period weightings could most likely have been predicted. Only the money market would produce low returns with such low volatility. The clone uses 91% of its portfolio to be put into cash and only 8% into skewness (The difference being rounding).

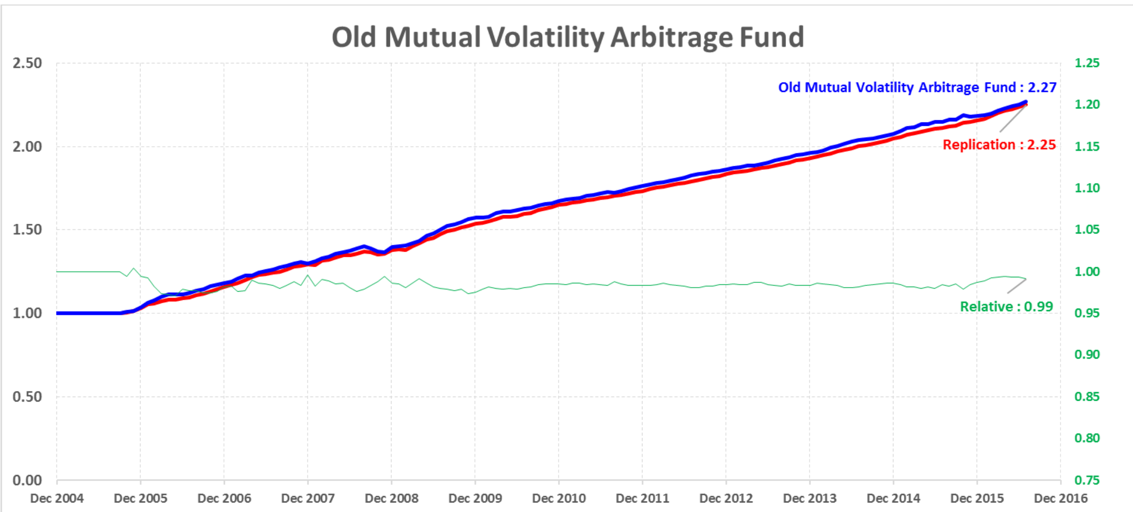
Figure 22: Old Mutual Volatility Arbitrage Fund Single Period Weighted Portfolio



0%	0%	0%	0%	0%	8%	0%	0%	0%	0%	0%	91%	0%
Momentum12m1	VOL5	BetaOLS60m5	ROE3	InterestCover3	Skewness1	R	N	CashflowToPrice1	DividendYield1	EarningsYield1	STF3M	J203

In line with the single period weighted portfolio, figure 23 which shows the Goodness of Fit replication, was near perfect with very little tracking error. The green relative curve remains comparatively level over the lifetime of the fund.

Figure 23: Old Mutual Volatility Arbitrage Fund Goodness of Fit



Figures 24 & 25 show the Old Mutual Volatility Arbitrage Fund's Mean and Median Weighted Styles respectively. The risk exposure of this fund is best described by almost 100% investment in the money market. This does not mean that the fund was actually invested in the money market but its chosen investment shared a similar return pattern and would therefore share a similar risk exposure.

Figure 24: Old Mutual Volatility Arbitrage Fund Mean Weighted Styles

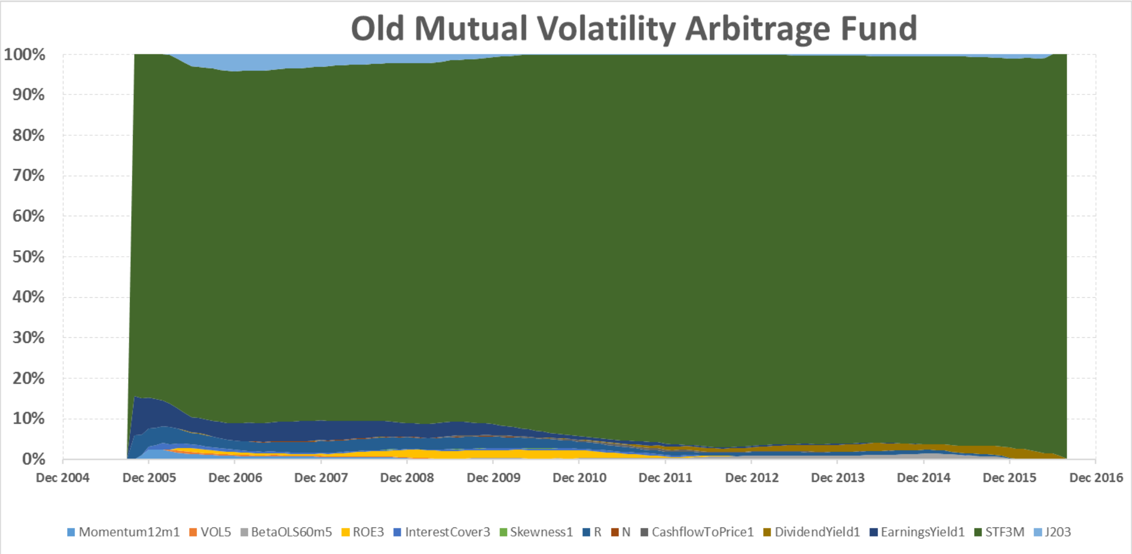
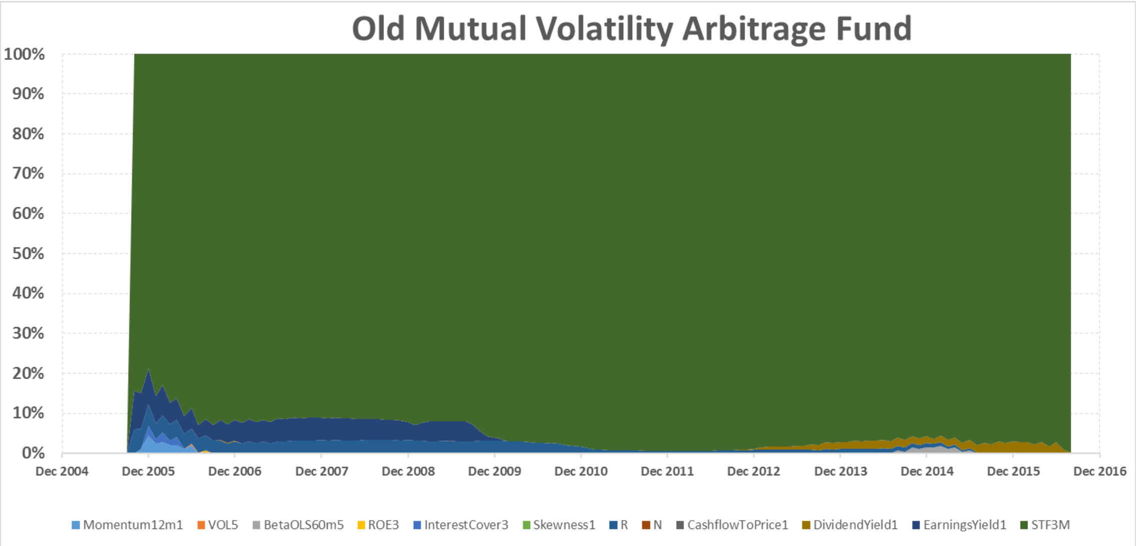
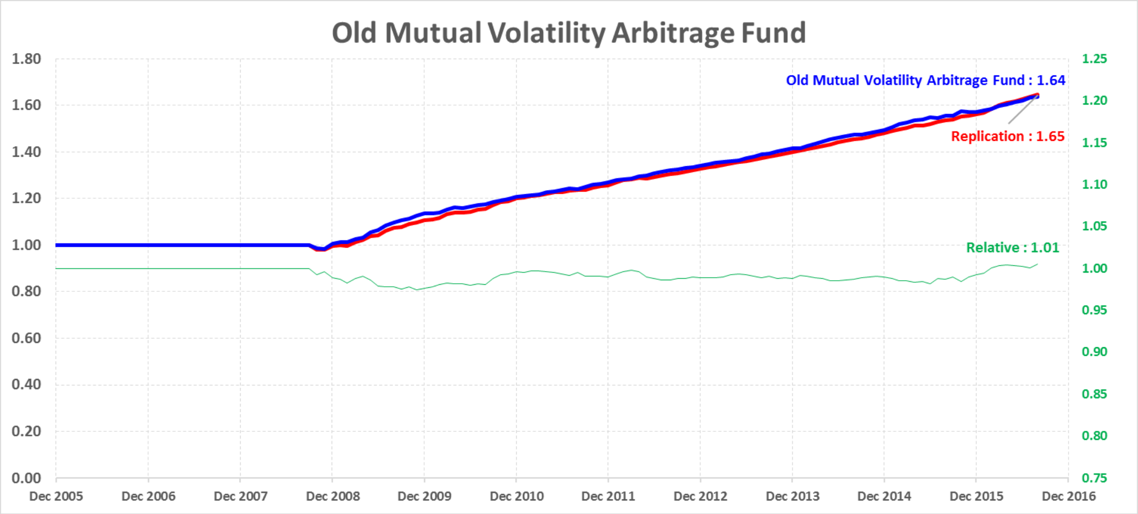


Figure 25: Old Mutual Volatility Arbitrage Fund Median Weighted Styles



Again, with such low volatility in the Old Mutual Volatility Arbitrage Fund's returns, figure 26 shows a near perfect out-of-sample replication.

Figure 26: Old Mutual Volatility Arbitrage Fund Out-of-Sample Replication

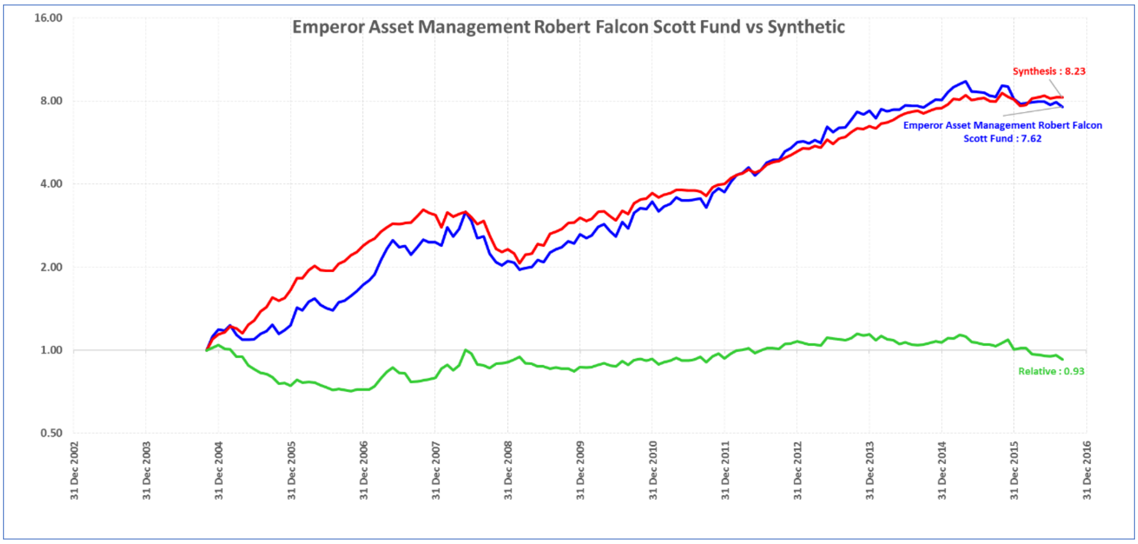


5.4.6 Emperor Asset Management Robert Falcon Scott Fund

The final displayed results are from the Emperor Asset Management Robert Falcon Scott Fund, with the Single Weighted Portfolio shown in figure 27. Unfortunately, this fund produced a poor single period weighted clone that contained large tracking errors with both under performance and over performance at various times. The fund's inception was on the 1st of November 2004 and even over the 12 years of results, there were few periods where the relative green curve between the clone and the fund was flat and hence imitating performance well.

Interestingly, the Robert Falcon Scott Fund's single weighted portfolio contained no cash. The fund's factor styles were split between momentum (37%), the JSE All Share Index (58%) and value in dividend yield (5%).

Figure 27: Robert Falcon Scott Fund Single Period Weighted Portfolio



37%	0%	0%	0%	0%	0%	0%	0%	0%	5%	0%	0%	58%
Momentum12m1	VOL5	BetaOLS60m5	ROE3	InterestCover3	Skewness1	R	N	CashflowToPrice1	DividendYield1	EarningsYield1	STF3M	J203

Figure 28 shows the Goodness of Fit replication for the Robert Falcon Scott Fund. This clone appears to imitate the fund's results well, however, upon closer inspection it did not track the fund's month to month movement very well at all. In fact, since the Robert Falcon Scott Fund produces highly volatile monthly returns, the clone merely smooths over these variations. This bears out through the relative green curve which did not show a consistent relative relationship.

Although the clone produced an accumulated return that was comparable to the fund, eventually outperforming it, the two curves do not track comparatively well and the clone was seen as poor.

Figure 28: Robert Falcon Scott Fund Goodness of Fit

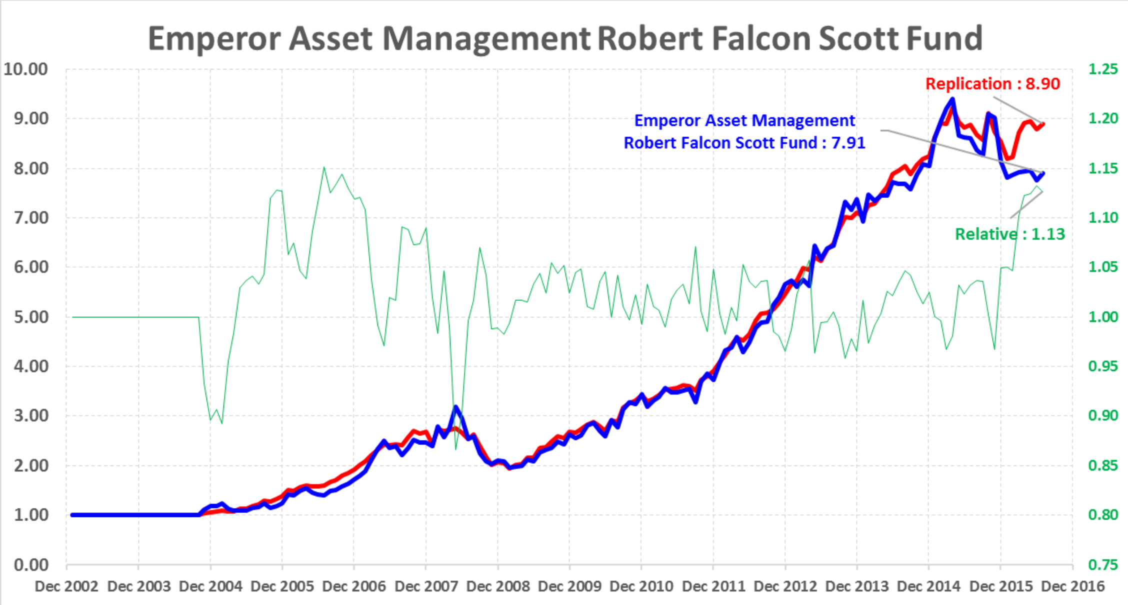


Figure 29 & 30, showing the Mean and Median Weighted Styles, bear out the findings from the Goodness of Fit graph. The number and size of the styles used in the clones would not be expected from a well-cloned fund. This was possibly due to two issues. First, the clone did not capture the true systematic risk within the fund which created a solution that merely had the best fit of variables. Alternatively, the fund does not have a consistent investment style and it evolves constantly. The weighted average approach used in this research would be insufficient in such a scenario as the clone would be influenced by a style up to three years in the past which could have no relevance to the fund's current investment style or strategy.

Figure 29: Robert Falcon Scott Fund Mean Weighted Styles

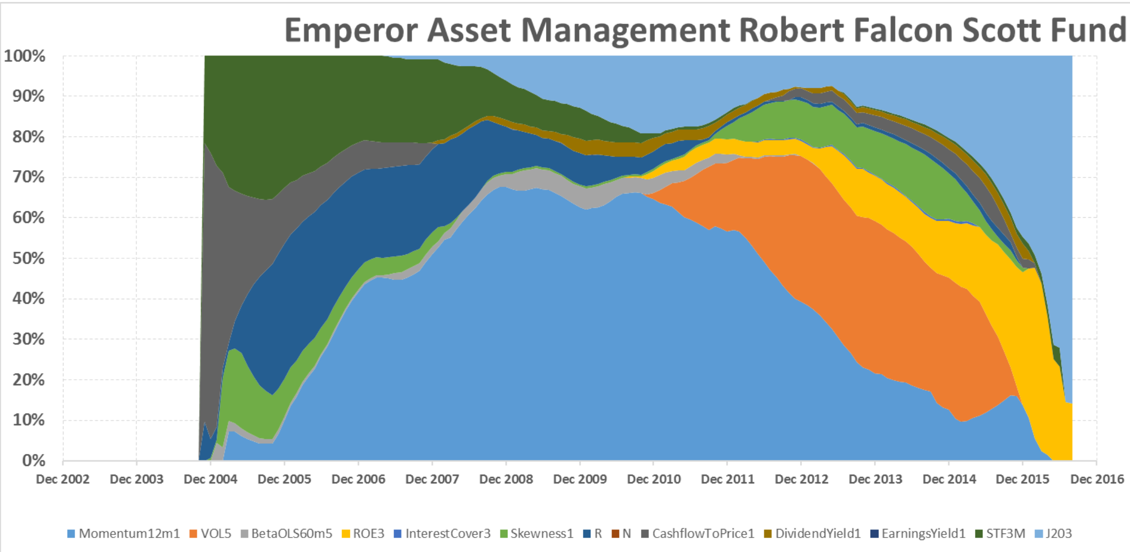


Figure 30: Robert Falcon Scott Fund Median Weighted Styles

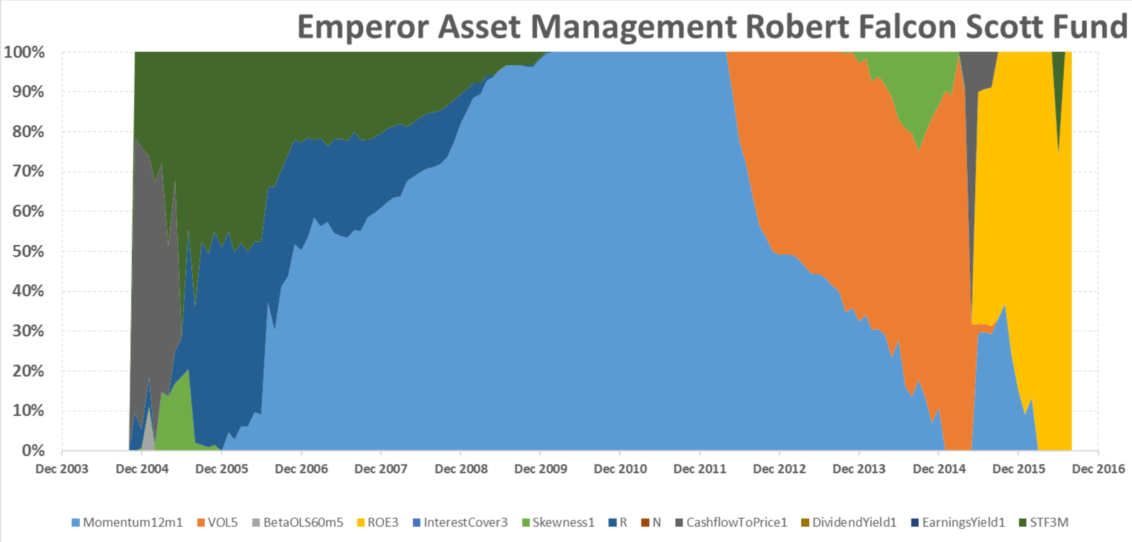
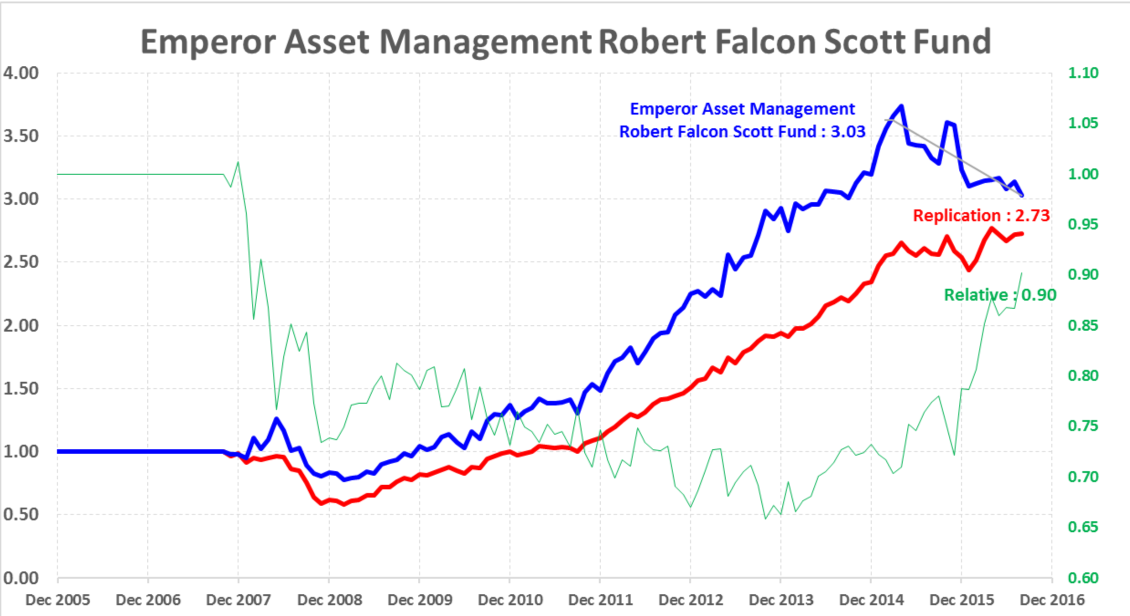


Figure 31 shows the Robert Falcon Scott Fund accumulated return performance against its Out-of-Sample Replication. As expected the clone was again poor. It was marred by general underperformance and extreme volatility. The green relative curve's constant spikes and continual upward and downward trends showed this. There was also a seemingly massive systematic break when the clone began in 2008. It is unclear whether this was due to the financial crises around this time or the ill-performance of the clone.

Figure 31: Robert Falcon Scott Fund Out-of-Sample Replication



5.4.7 Summary of Fund Results

Table 2 shows a summary of all the replication analyses that were carried out on the sample of hedge funds, including the HNALSI and the other individual fund results already presented in this chapter.

It should be noted that over 91% (32/35) of the goodness of fits replications were rated as reasonable or better. Additionally, 76% (19/25) of the out-of-sample replications were also rated as reasonable or better. Unfortunately, ten of the out-of-sample clones were only run for a year or two and thus did not have enough results to be considered. They required at least three years (36 data points) of monthly return history just to build the clone but many only had a year of history beyond that. There were a high number of poor single period weighted portfolios 12 out of 36 (33%).

Table 2: Summary of Replication Fits

	Good Replication	Reasonable but flawed	Poor	Lack of data
Single Period Weighted Portfolio	12	11	12	
Goodness of Fit	16	16	3	
Out-of-Sample Replication	6	13	6	10

5.5 Efficient Frontier

Figure 32 plots the annualised returns and standard deviation of sample over the most recent three-year period. As discussed in Chapter 4, an efficient frontier curve has been plotted. This was determined by creating portfolios of hedge funds with the lowest volatility given a particular annualised return amount.

A risk-free return rate of 7% was assumed. The capital allocation line was then plotted from the risk-free rate to a tangent against the curve. This point of intersection is called the optimal portfolio. From these results the optimal portfolio should generate an annualised return of 15.98% with a standard deviation (volatility) of 2.73%. The capital allocation line produced a Sharpe ratio of 3.29.

Figure 33 shows a breakdown of the optimal portfolio. It would consist of nine funds in total, but predominately only two, namely, the Peregrine Pure Hedge Fund and the Corion Prosperitas Hedge Fund which would make up over 65% of the portfolio. Table 3 shows the breakdown of the optimal portfolio by styles within each fund.

Figure 32: Annualised Returns vs Volatility of South African hedge funds over last 3 years

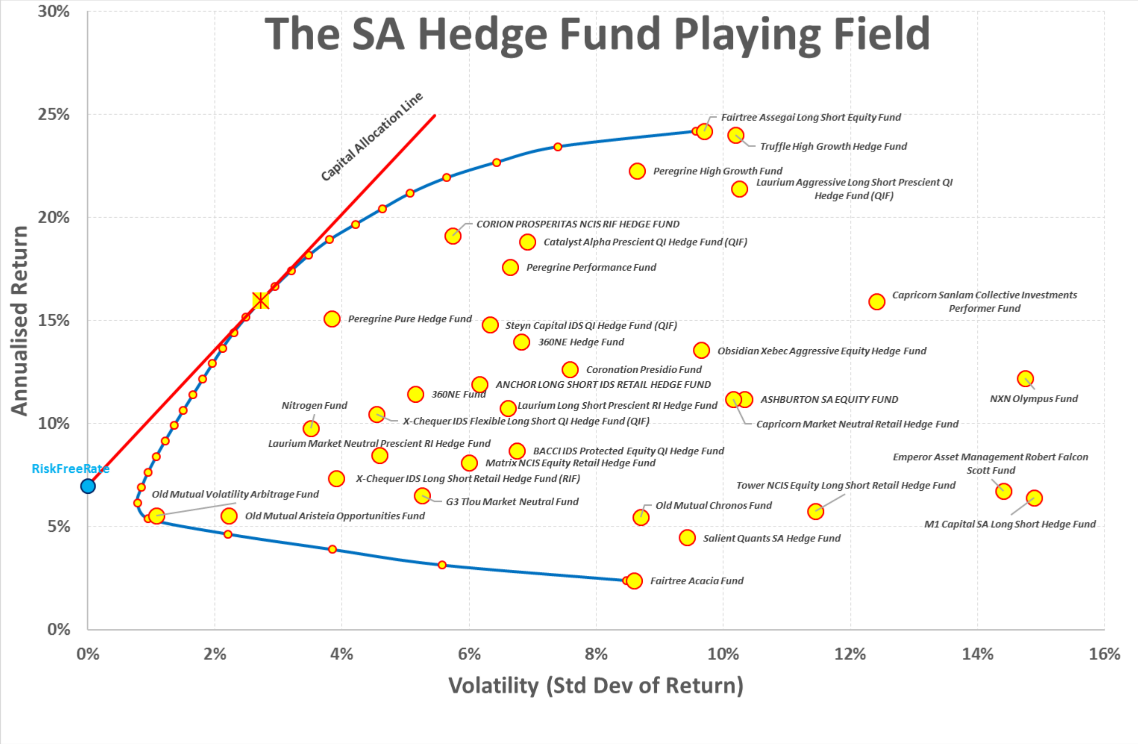


Figure 33: Weightings of funds that comprise the optimal portfolio

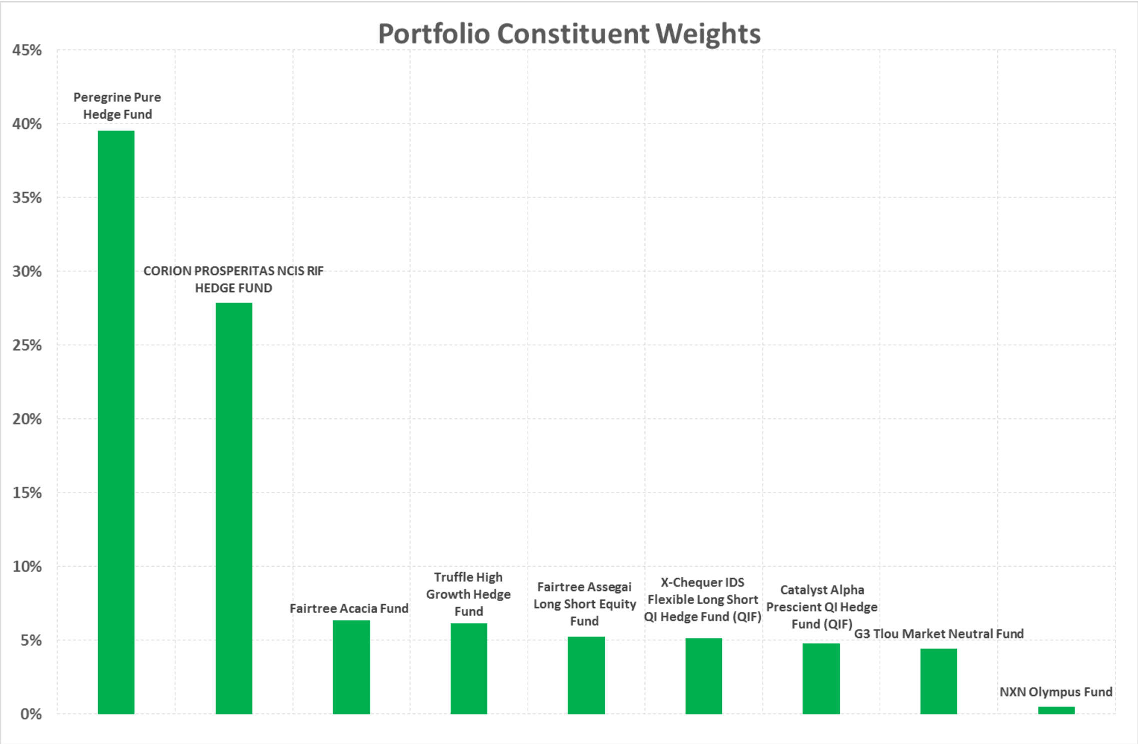


Table 3: Optimal Portfolio Style Weightings

Hedge Funds	Momentum12m1	VOL5	BetaOLS60m5	ROE3	InterestCover3	Skewness1	R	N	CashflowToPrice1	DividendYield1	EarningsYield1	STF3M	J203	Weighting
Peregrine Pure Hedge Fund	20	20	20			15						25		39.55%
CORION PROSPERITAS NCIS RIF HEDGE FUND	40		50			10								27.87%
Fairtree Acacia Fund						5	15					80		6.36%
Truffle High Growth Hedge Fund	60	15	25											6.14%
Fairtree Assegai Long Short Equity Fund	50		50											5.23%
X-Chequer IDS Flexible Long Short QI Hedge Fund (QIF)		25				20	10					45		5.13%
Catalyst Alpha Prescient QI Hedge Fund (QIF)	20	10	65			5								4.80%
G3 Tlou Market Neutral Fund												100		4.43%
NXN Olympus Fund	25	50										25		0.49%
Optimal Weightings	**26.44**	**10.84**	**29.11**	**-**	**-**	**10.30**	**1.47**	**-**	**-**	**-**	**-**	**21.84**	**-**	**100**

Chapter 6 – Discussion of Results

6.1 Introduction

The research results presented will be discussed in detail with reference to the main research question as well as the supporting questions as listed in Chapter 3. The supporting questions will be covered first as their results feed directly into answering the main research question.

The research covered a total of 34 hedge funds and 1 index, all of which met the minimum criteria to be part of the sample. Although all of these results were not presented in Chapter 5, this discussion will speak to the results in their entirety with only direct reference made to the funds already presented.

6.2 Supporting Research Question: Which style factors are representative of the systematic risk contained within the different hedge funds and index?

Simply put, Table 1 shows the style factors which are prevalent in your average equity-based hedge fund within South Africa. From a hedge fund performance perspective, it was extremely underwhelming that roughly 39% of monthly returns can be imitated through investing in the money market alone. This does not mean that the hedge funds in South Africa are necessarily putting a large share of their investors' money into the money market. What it does mean, however, is that they are choosing investments with similar returns to the market and consequently a similar risk profile.

The almost perfect replication of the Old Mutual Volatility Arbitrage Fund (figure 23) is comprised entirely of a cash like investment (figures 24 & 25). So much so that it is very likely that the fund is in fact heavily invested in the money market. However, it was funds like these which have skewed the mean style weightings so heavily in the descriptive statistics. These cash dominated funds tended to be ones with the lowest annualised returns as well as lower volatilities as seen in figure 1.

Most of the hedge funds have very polarised style weightings. The results shown are fairly typical of the entire sample, in that one to three styles dominate at any one time. This can be seen more easily when looking at the median weightings which help filter out the smaller and less significant styles for that fund. Ultimately this speaks to each fund tending to have a clear and focused investment strategy.

With some of the funds, this investment style has persisted since its inception. The Peregrine High Growth Fund, in figure 10, has shown itself to be a strong momentum focused fund while the 36ONE Fund, in figure 15, has largely been a low volatility / cash fund with a short period of momentum. Others have shown clear changes in their investment strategy. The Coronation Presidio Fund, in figure 20, began with a value (dividend yield) / cash style but at the beginning of 2011, switched to a distinctive low volatility style.

This research was not focused on outperformance or trying to establish which funds achieved the best returns. However, when focusing on the funds which have yielded the higher annualised returns, a clear pattern emerges. As per table 1, the next two most prominent factor styles of momentum and low volatility, featured extensively in the styles of these higher yielding funds. These two styles feature without exception in all the hedge funds that have annualised returns above 20%.

In chapter 5 the extremely low medians of these two important styles were highlighted. The relatively poor performance of many of the sample hedge funds was not considered surprising when it was discovered that more than half of the data points from the sample contain no low volatility or beta styles and 50% contained a 7.6% weighting or less of momentum.

The rolling window weighted styles were given more bearing than single period weighted styles as the analysis needed to account for the time-variations in the factor exposures (Amenc et al., 2008). Ultimately hedge funds evolve and adapt their strategies over time. A fixed portfolio would struggle to represent this changing risk exposure over the long term.

All of the above is backed up by the HNALSI results as shown in figures 4 and 5. Amongst others, it does suffer from selection as well survivorship bias (C. S. Asness et al., 2001; Fung & Hsieh, 2006) in that the submission of data from its constituents is voluntary and often sporadic. However, the HNALSI remains the best overall snapshot of all the equity focused hedge funds within South Africa. And the index does show cash, momentum and low volatility as the most significant styles over the last 10 years. Both value, in the form of ROE, and skewness were also role players for limited periods of time.

Ultimately, the fact that the most dominant style was an investment in the money market means that many hedge funds for the last 15 years have been looking for consistent returns with lower risk but at the expense of maximising their returns.

6.3 Supporting Research Question: How closely do the optimal models replicate the performance of hedge funds and index in-sample?

Overall, the in-sample clone performances did bare out as expected. As already highlighted from table 2, the Goodness of Fit replications were excellent, with all but three fund clones being regarded as, at least, reasonable imitations of performance.

The Single Period Weighted Portfolios were also mostly reasonable but had many more poorly rated performances as they would suffer systematic breaks over the long term. These breaks were either due to shocks to the financial system which the clone was unable to adapt to or due to significant changes to investment strategies in the funds themselves. During times of financial duress, such as the financial crises of 2007/2008 and the financial minister fiasco during December 2015 (Hogg, 2016), the static nature of the single period clone generally results in huge difference in performance from the fund itself. This difference is caused by a rapid defensive change in strategy, perhaps even on a short term basis, that the clone is unable replicate. Alternatively, the fund and style strategies may remain aligned but since the clone only approximates the risk exposure of the hedge in a static environment, this risk exposure may react differently in times of stress (Fischer et al., 2016; Kat, 2007).

In the displayed fund results, especially the Peregrine High Growth Fund, the Coronation Presidio Fund and the Robert Falcon Scott Fund, it can been see how each of the single period weighted clones struggle to imitate the month to month returns of each fund due to their evolving investment styles (figures 9, 19 & 29). However, they do manage to generate equivalent accumulated returns over the lifetime of the funds.

The goodness of fit replication was designed to overcome the shortfalls of the single period weighted clone, namely to be able to adjust to the changing styles of the fund over time. This difference in performance can be seen when contrasting the single and multi-period clone performance of either the Peregrine High Growth Fund or the Coronation Presidio Fund. These funds experienced rapid changes to their investment styles as seen in their Average Weighted Style graphs, yet the Goodness of Fit clones were able to adjust accordingly.

However, these clones are not without their weaknesses either. The Peregrine High Growth Fund Goodness of Fit graph (figure 8), although replicating the distributional properties of the returns accurately, shows a steady underperformance over the entire life of the fund. Over a 15-year period this does lead to a significant difference in accumulated returns of almost 25%, although the researcher does regard the replication as very reasonable due to its ability to replicate the volatility (risk).

The reasoning for this underperformance cannot be deduced easily from the results. However, one of the key assumptions for this research, based on the literature, was that only the beta (alternative) or systematic risk could be cloned and that many hedge funds today produce very little true alpha (Kooli & Sharma, 2012). However, logic dictates that the fund with the highest annualised returns within the sample, but only a relative medium amount of risk or volatility, is most likely generating part of its returns from the fund manager's skill or alpha. It is unlikely to be extracting its returns from systematic risk alone. And since the clone cannot replicate the Peregrine High Growth Fund's alpha, it experienced under performance.

The other reason for such a consistent difference in performance could be due to inappropriate factor styles that were unable to fully describe the systematic or beta risk to which the hedge fund was exposed (Amenc et al., 2008). This remains one of the chief criticisms of the factor approach to replication.

Another weakness of the Goodness of Fit replication is the lag effect created by using a weighted average of styles. This does not cause a problem when funds have a consistent style or change styles gradually over a period time. Such funds from the results presented include the 36ONE Fund and the Old Mutual Volatility Arbitrage Fund which show extremely consistent investment styles over time (figures 14 & 24). However, when a fund's style is constantly shifting and does so dramatically, this results in an under performance of the clone as the weighted averaged style being used is still affected by styles used in the fund from up to three years previously. This is most likely what happened with the Robert Falcon Scott Fund's clone (figure 28). Although it captured the overall accumulated returns relatively well, it failed to imitate or mirror the volatility within the fund.

It must be reiterated that the Goodness of Fit replication is best used to understand the nature the of a hedge fund or index. The replication itself acts with hindsight of the returns to come and thus has a built-in "look-ahead bias" (Hasanhodzic & Lo, 2007). In its current form, the Goodness of Fit clone does not provide a good prediction of the future returns out-of-sample. As much of the research agrees, using average past exposures combined with a linear regression technique is bound to result in poor performance (Amenc et al., 2008).

However, a lot of these weaknesses relating to the factor replication of individual hedge funds can be avoided by using portfolios of hedge funds, fund of funds or hedge fund indices where most of the individual risk is diversified away (Kat & Palaro, 2006). Looking at the Goodness of Fit for the HNALSI in figure 3, this appears to hold true. The clone imitates the index almost perfectly, both in accumulated returns as well as the distribution of those returns. This is despite the variety of changing styles which may influence the clone's performance. There is, however, a sizeable systematic break down in the clone which yet again coincides with the massive financial hit the South African market took due to the axing of successive finance ministers in December 2015 (Hogg, 2016). With the factor-based approach's dependence on historical data to predict future returns, this creates an inherent problem in times of market turbulence such as this (Fischer et al., 2016).

6.4 Supporting Research Question: How closely does the optimal model replicate the performance of the hedge funds and index out-of-sample?

Similar to the goodness of fit replications, as already identified in table 2, the out-of-sample clones performed well with only a few replications being regarded as poor imitations of their benchmark funds. In contrast, however, far more of the clones did contain some weakness or flaw and unfortunately over a quarter of the funds in the sample could not produce usable clones as they did contain enough history.

While the out-of-sample clones seemed to have fewer large systematic breaks than the goodness of fit replications, there was a far wider spread of general under performance in each of the clones. In fact, four of the five fund clones with displayed results achieved sub-par accumulated returns against their respective hedge funds. The only exception was the Old Mutual Volatility Arbitrage Fund, but with such a heavy weighting towards the consistency of returns from the money market, this is not surprising.

The reasoning for this under performance has already been highlighted, in that a reliance on using average past exposures in order to predict future exposure is bound to produce poor out-of-sample results (Amenc et al., 2008). However, this research did attempt to develop a more dynamic factor model which would be able to capture these time-varying factor exposures.

The problem lies within the nature of the data. The return data currently provided by the hedge funds are monthly returns. This means that a year's worth of returns is only made up of 12 data points. For this research, 11 factor styles were used in order to ensure that the relevant styles, and hence risk, for each fund could be captured and their performance replicated. In order to create a workable regression solution using 11 degrees of freedom, the researcher decided to use 36 data points for each weighted portfolio. This ultimately means that each style weighting is based on three years of old data.

In order to reduce the bias created by possible irrelevant historical data, the styles were weighted in order to give more importance to the most recent data points and less to the older data points. However, even the most recent data point could be regarded as out-of-date and no longer relevant. For each month of return data contains roughly 22 business days of data. And as such the most recent monthly return contains some daily returns which are already almost a month old. With the speed at which financial markets can be moved by a single piece of news within a single day, only rebalancing the clone on a monthly basis means that the replication is based on old data and styles which may no longer be applicable.

The clones have, for the most part, captured the inherent nature of the investment styles within each fund as well as their overall distributional properties. But it is due to this lag effect created by the persistence of older styles that the clones have shown general underperformance across the sample.

Even the clone of the HNALSI, in figure 6, shows a consistent under performance of returns over the entire lifespan of the index. Generally, an index should show better out-of-sample results than individual hedge fund due to the diversifying out of the individual risk and thus a presence of only systematic risk (Kat & Palaro, 2006). This further emphasises the weakness of monthly data for the out-of-sample clones.

6.5 Supporting Research Question: What is the optimal level of risk versus return that hedge funds in South Africa should look to seek?

The hedge fund sample has a large spread in terms returns and risk. In figure 1, the annualised returns range from 5% to 29% while the risk ranges from as low as 2% all the way to over 19%. This research used portfolio theory (Markowitz, 1991) and constructed an efficient frontier curve in order to establish the optimal rate of return versus risk which equity hedge funds should look to seek within South Africa. As explained in chapter 4, only the last three years of returns were used.

Figure 32 shows a slightly narrower spread than the full annualised returns but it has a fairly similar spread in results. The optimal portfolio return of 15.98% appears to be low when compared to the funds with the highest return of around 24% but is far less risky with a volatility of only 2.73% versus the 10% of the high return funds.

The composition of this optimal portfolio is shown in figure 33, but in order to create such a portfolio without physically investing in those funds, one could create a clone using the weighted styles of those funds in the appropriate ratios. Unfortunately, this portfolio was not calculated with the use of the "style engine" for this research. However, a close approximation of the relevant styles can be made using average and median weighted style graphs for only the most recent 3 years.

Table 3 is the result of this approximation which shows the style weightings for the optimal portfolio. Based off this research's results, any equity hedge fund within South Africa today should be looking to create a portfolio that exhibits a style with roughly 26% momentum, 40% low volatility (vol5 + beta), 2% resources, 10% skewness and 22% in the money market.

6.6 Main Research Question: Can the returns of hedge funds in South Africa be replicated through long only investing in the equity market?

Replication of hedge funds can be defined in one of two ways. The clone could produce equivalent returns to the fund or index in absolute terms, meaning they were equal in all measures and essentially mirror the returns. Alternatively, they could be equal in distribution, meaning that the clone matches the fund in terms of statistical properties with the exception of the mean or average (Amenc et al., 2008; Fischer et al., 2016). This research has chosen the stricter first definition.

Additionally, a clear distinction needs to be drawn between replications in-sample and those out-of-sample. In-sample replication has bias built into the clone as the entire dataset is known and as long as the appropriate factor styles have been chosen, becomes a case of merely finding the best fit. However, they are still extremely useful as a way of disseminating the styles of a hedge fund and understanding the nature of its beta exposure.

On the other hand, out-of-sample replication involves the idea of using a clone to predict the future performance of a hedge fund based on historic data and return performance. This should be the end goal of all replication work as it moves the more academic and theoretically focused in-sample replications into a practical application within the business environment. The focus of this research is to develop out-of-sample models which are practical and applicable in the business environment.

With those definitions in mind, the answer to the main research question cannot be an unreserved yes based on the results. Although many of the replications performed well, too many of the out-of-sample clones contained flaws or underperformed to some degree. However, the in-sample clones did imitate their funds with minimal tracking error and provided a great insight into their investment styles.

This research did not manage to consistently create out-of-sample clones that imitated both the absolute returns, as well their distributional properties, using long only equity factors. However, this research did not prove that it was not possible. As already highlighted, the structure and tools used in this research contained many limitations, many of which did have an effect on the final results. When considering all the limitations within the methodology, the results were extremely positive and show a fair degree of success.

Chapter 7 – Conclusion

This chapter gives a brief overview of the findings, in addition to the limitations with recommendations on improvement as well possible areas of future study.

7.1 Summary of Findings

For the last 10 years in South Africa, hedge fund returns have surprisingly displayed a large systematic risk equivalent to those shown by the money market. In fact, around 39% of the mean returns display a style equivalent to cash. The next two most prevalent styles are momentum and low volatility, each making up around 18% of the mean styles. These latter two styles, however, have been more dominant in the higher yielding hedge funds and consequently have been the “best” styles over this time period.

This research generally produced excellent in-sample clones. They imitated the performance of the sample hedge funds very well, both in terms of accumulated returns and distributional properties. The multi period rolling window portfolios were shown to be far superior to the single period weighted portfolios. Some of the clones of the better performing hedge funds under performed significantly. It was deemed that since part of these returns cannot be replicated, then not all of their exposure is alternative beta. Thus, in contrast to the assumption made in this research, they must contain some portion of alpha (Jaeger & Wagner, 2005; Kooli & Sharma, 2012).

The out-of-sample clones’ performance was less impressive. Many of them showed severe underperformance which was attributed to the lag effect created by the weighting. This was especially prevalent in funds which showed a constant shift in their investment style which the clones were unable to adjust to quickly enough.

Both types of clones displayed systematic breaks in their performance, often coinciding with times of market stress, especially the financial crisis around 2008 and the turmoil created by the finance minister turmoil at the end of 2015 (Hogg, 2016) This remains a weakness of passive funds as the systematic risk of the funds is only imitated through an established linear relationship which can break during such market disruption (Jaeger & Wagner, 2005).

Through portfolio theory (Markowitz, 1991) and the creation of an efficient frontier curve the optimal style weightings were established. Unsurprisingly, low volatility and momentum featured prominently with weightings of 40% and 26% respectively. The balance consisted of cash and skewness.

Overall, the replications were able to accurately display the systematic risk exposure of the sample of hedge funds as well as their evolving styles. However, the methodology for the out-of-sample replication still requires a significant amount of work.

7.2 Research Limitations, Recommendations and Future Areas of Study

In the construction of this research, certain assumptions and limitations were created in order for the focus to remain on the study of the relationship between the style factors, their corresponding systematic risk exposure and the returns of the hedge funds. Additionally, further limitations or weaknesses were discovered through the research which could possibly influence the effectiveness of the replications and analysis performed. A brief summary of these limitations and observations have been included below:

A founding assumption for this research was that modern hedge funds lack alpha and only composed of systematic or alternative beta. This is required since true alpha is not replicable (Jaeger & Wagner, 2005).

The impact of transaction costs has been ignored for this research. The researcher has made the assumption that they would be negligible although no firm stance has been established.

The relationship between the factor styles and hedge fund returns was assumed to be linear. However, since fund managers use highly dynamic trading strategies and mechanisms, this can possibly produce non-linear and non-normal relationships (Kat, 2007).

The analysis was limited to using own long-only equity styles to prevent overfitting and thus poor out-of-sample replication performance (O'Doherty et al., 2016). Equity styles were needed due to the use of the “style engine” which currently uses JSE share data.

The South African hedge fund industry is relatively young and small compared to the industry globally which means there is a limit to the volume of data available. Many funds failed to meet the minimum three-year criteria which further limited the number which qualified for the sample.

This research is focussed on the hedge fund industry in South Africa before the full implementation of CISCA in October 2016. The classification of hedge funds now as “collective investment schemes” has huge potential implications for the industry which could see a large portion of the R1.8 trillion collective investment scheme industry flow to hedge funds (McClelland, 2016).

The monthly return data used to create the replications was a massive unanticipated limitation. The rolling windows used for the Goodness of Fit as well as the Out-of-Sample Replication used 36 data points for each window. This was based off the model using 11 degrees of freedom (style factors). Since the return data is only monthly, this means each window covered 3 years of styles. Many of the fund’s styles evolved completely in far less time which meant the replications lagged behind as they had remnants of older styles in their composition.

Based on these weaknesses and limitations, there are many recommendations which could be made to improve the cloned funds some of which could be included in further research.

As a result of hedge funds being included under CISCA, retail funds are now required to be valued on a daily basis (KPMG, 2015). This means that instead of monthly return data, future studies of this nature could be carried out with daily return data. Thus, instead of three-year rolling windows, windows of just one-and-a-half months could be created without having to reduce the number of data points or style factors. Using more recent data would lead to more accurate out-of-sample clones even for a fund that constantly evolves its investment style.

This research created extremely passive and systematic clones that were at the mercy of shocks to the market which might upset the linear relationship of the selected styles to the systematic risk of the hedge funds. This can be partly negated through the use of daily data as suggested above. In reality, a slightly more active role will need to be taken by the fund manager in managing the passive clone, especially around periods of great uncertainty in the market.

The styles selected for the research were shown to be largely representative of the systematic risk exposure of the hedge funds within the sample. However, only the best performing segment of each style was used for the clones. This made the assumption that each fund was making the most optimal and efficient investment decisions which would not always be the case. Any future research should look to expand the styles selected, but also include some of the lesser performing segments of the selected factors so as to capture these inefficient investment decisions.

And lastly future research should look to understand what the investors within hedge funds are looking for from their investment. Are they merely looking to maximise their return or are they more interested in creating a diversified portfolio with a specific exposure to certain types of risk? Their incentive for investing with hedge funds could lead to a better tailored replication which would satisfy their requirements.

7.3 Final Thoughts

Ultimately, maybe the wrong questions of hedge fund replication are being asked? Perhaps passive funds should not be looking to imitate performance both in mean returns and distributional properties, at a lower risk, which this research showed was difficult and currently unable to do so. Possibly they should be offering a cost-efficient way for investors to access different and alternative beta exposure (Amenc et al., 2010).

In fact, this is starting to happen already with the offering of new factor ETFs or “smart beta” growing worldwide, with the industry currently worth $316bn and forecast to cross the $1tn mark by 2020 (Wigglesworth, 2016). It seems factor style replication is soon to become mainstream.

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Appendix 1

FundName	Volatility	Return
360NE Fund	4.65%	16.71%
360NE Hedge Fund	8.60%	19.19%
ANCHOR LONG SHORT IDS RETAIL HEDGE FUND	5.86%	11.76%
ASHBURTON SA EQUITY FUND	9.69%	15.88%
BACCI IDS Protected Equity QI Hedge Fund	6.72%	11.09%
Capricorn Market Neutral Retail Hedge Fund	9.12%	12.93%
Capricorn Sanlam Collective Investments Performer Fund	12.03%	23.35%
Catalyst Alpha Prescient QI Hedge Fund (QIF)	13.14%	20.54%
CORION PROSPERITAS NCIS RIF HEDGE FUND	5.76%	21.83%
Coronation Presidio Fund	8.79%	17.76%
Emperor Asset Management Robert Falcon Scott Fund	19.32%	18.69%
Fairtree Acacia Fund	14.48%	19.89%
Fairtree Assegai Long Short Equity Fund	8.66%	25.10%
G3 Tlou Market Neutral Fund	4.67%	7.50%
Laurium Aggressive Long Short Prescient QI Hedge Fund (QIF)	11.29%	27.60%
Laurium Long Short Prescient RI Hedge Fund	7.46%	13.09%
Laurium Market Neutral Prescient RI Hedge Fund	4.06%	10.84%
M1 Capital SA Long Short Hedge Fund	14.11%	11.71%
Matrix NCIS Equity Retail Hedge Fund	5.88%	8.39%
Nitrogen Fund	4.65%	14.51%
NXN Olympus Fund	17.18%	17.81%
Obsidian Xebec Aggressive Equity Hedge Fund	14.95%	14.36%
Old Mutual Aristeia Opportunities Fund	1.86%	6.00%
Old Mutual Chronos Fund	8.33%	5.50%
Old Mutual Volatility Arbitrage Fund	1.98%	7.93%
Peregrine High Growth Fund	10.60%	29.05%
Peregrine Performance Fund	6.62%	18.98%
Peregrine Pure Hedge Fund	6.97%	22.77%
Salient Quants SA Hedge Fund	8.38%	10.59%
Steyn Capital IDS QI Hedge Fund (QIF)	6.58%	19.69%
Tower NCIS Equity Long Short Retail Hedge Fund	10.08%	14.06%
Truffle High Growth Hedge Fund	13.14%	26.70%
X-Chequer IDS Flexible Long Short QI Hedge Fund (QIF)	4.74%	15.07%
X-Chequer IDS Long Short Retail Hedge Fund (RIF)	5.29%	14.13%

Appendix 2

Ethical Clearance

Dear David Boers

Protocol Number: **Temp2016-02011**

Title: **Optimal Composition of Hedge Fund Replicators in Africa**

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

You are therefore allowed to continue collecting your data.

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

Kind Regards,

Adele Bekker