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Optimising a portfolio of hedge funds in South Africa

by

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Abstract

The South African hedge fund industry is reported to have had R52 billion (USD 4.8 billion) assets under management at the end of December 2013. This compares to the global industry which is reported to have surpassed USD 2.6 trillion at the end of 2013. Due to the relative infancy of the local industry, little research exists to analyse the performance of South African hedge fund strategies. This study focuses on the performance of South African hedge fund strategies under different market regimes, taking into consideration market and economic factors specific to South Africa. The analysis shows that the hedge fund strategies offer a diversification benefit to more traditional asset classes, and the results of the study can be used to inform an investor's allocation decision.

The findings of the analysis are used as the basis of a portfolio construction framework for constructing a portfolio of hedge funds. The framework is predicated on the investor having a view on the forthcoming macro environment. The framework enables the investor to identify funds and strategies that have produced a stable alpha over a similar market regime for inclusion in the portfolio of funds. After identifying those funds and strategies most suited to the anticipated macro environment, the number of funds to be included in the portfolio is taken under consideration to determine the optimal number such that the performance and risk characteristics of the portfolio are not compromised. The analysis takes the higher moments of the distribution into account to cater for the non-normal nature of hedge fund distributions.

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Chapter 1: Introduction

Introduction to the field of analysis

The South African hedge fund industry is still in its infancy when compared to its global counterpart. Estimates on the size of the industry vary as many successful and closed funds are not included in the various hedge fund indices, and there can be a level of double counting between single manager funds and fund of hedge funds. HedgeNewsAfrica[1] reported a peak in assets at R52 billion (USD 4.8 billion) at the end of December 2013. This compares to the global industry, which Preqin[2] reported global hedge fund assets under management to have surpassed USD 2.6 trillion at the end of 2013.

There is a wide range of investment strategies that hedge funds can use to generate returns. Many of these strategies hedge against market downturns, and tend to be classified as absolute return strategies. This means that they aim to produce positive returns regardless of market cycles.

Markowitz identified the trade-off facing the investor of maximising return while minimising the associated risk. The top three reasons for investing in hedge funds are typically diversification, due to their low correlation to traditional portfolios of cash, bonds and equities and their ability to profit during both rising and falling

[1] HedgeNews Africa is a South African based hedge fund publication. The online publication can be accessed at http://www.hedgenewsafrica.com

[2] Preqin is a leading source of data and intelligence for the global alternative investment industry. Website: https://www.preqin.com/

markets, composite portfolio strategy enhancement and dampened portfolio volatility (Gantz (2013)). However, research of the performance of global hedge fund strategies in bull and bear markets has been inconsistent. The research conducted by Sandvik, Fryedenberg, Westgaard and Heitman (2011), Capocci, Corhay and Hubner (2003) and Edwards and Caglayan (2000) on the performance of hedge fund strategies in bull and bear markets, all found that hedge funds created superior risk adjusted returns in bull periods but lacked evidence to support any superior performance in bear markets. However, the findings regarding which strategies offered the best alpha generation in these periods differed across studies. These studies were conducted across the global hedge fund strategies. There is currently no research available on the performance of South African hedge fund strategies in different macroeconomic environments. This is a considerable knowledge gap for the South African industry as local funds will take exposure to local securities which are more sensitive to the South African economic environment than to global influences.

Globally, there are in excess of 10 distinct investment strategies. Locally, the hedge fund universe is a lot smaller and can broadly be divided into four main strategies. Within these classifications, hedge fund managers employ a wide variety of strategies to generate returns. Managers may employ leverage, shorting, arbitrage, derivatives and other hedging techniques in an attempt to increase the return profile of a portfolio and reduce risk and volatility. The main hedge fund strategies utilised in South Africa include the equity long short, equity market neutral, fixed income arbitrage and multi-strategy disciplines. Equity long short is the most common

strategy in South Africa accounting for more than 52% of industry assets (Novare[3], 2013). This strategy will go long securities that are expected to appreciate in value, while short selling securities that are expected to decrease in value. This style is therefore able to profit from both rising and falling markets. Equity market neutral funds follow a similar investment strategy to equity long short with the exception that the long and short exposures are taken in companies that are exposed to similar economic factors and the long and short exposure are approximately equal making the strategy more agnostic to market direction than the equity long short style. Fixed income arbitrage funds exploit price discrepancies in fixed income instruments such as bonds, interest rates swaps and forward rate agreements. In this strategy, long and short positions are entered into in mispriced fixed income instruments with the expectation that these exposures will revert to a fair value in time. Multi-strategy hedge funds provide a diversified return profile by investing across a range of hedge fund strategies, such as equity long short, equity market neutral and fixed income arbitrage. Asset allocation between strategies is managed within the fund to take advantage of market moves and provide a better risk adjusted profile. Quantitative strategies also have a place in the South African market, but are limited in both number of funds and the assets under management. Broadly speaking, these strategies use purely quantitative techniques to assess the behaviour of shares, and look to profit based on signals generated from quantitative or statistical analyses.

[3] Novare Investments is a South African based asset manager who compiles and publishes an annual report on the South African landscape. The cited survey is available at http://www.novare.com/uploads/files/SAHedgeFundSurvey2.pdf

Investment returns, volatility and risk differ significantly among the various hedge fund strategies.

Investors have several options available for accessing hedge funds. The first is to directly invest in one or several hedge funds, and another is to invest via a fund of hedge fund structure, a multi-management approach whereby the fund of hedge fund provider will invest in a range of single hedge fund strategies to create a desired return profile. The fund of hedge fund specialised has sufficient expertise and experience on the range of complex strategies, and provide calculated diversification and active risk management (Jones, 2007. Novare reported in their latest annual survey that the fund of hedge fund industry continues to be the largest allocator of funds to the single managers accounting for 63% of industry assets as fund of hedge funds remain the investment vehicle of choice for most South African institutions and pension funds**.**

Research on the performance of South African hedge fund strategies is not available; and Markowitz' classical mean-variance optimisation technique remains the most commonly applied optimisation tool despite the non-normal nature of hedge fund return distributions. Davies, Kat and Lu (2004) showed that by ignoring the higher moments of these distributions, the risks associated with these asset classes are not appropriately accounted for. Any portfolio construction utilising this framework will therefore be inefficient in the allocation of risk across securities. This study will factor in the behaviour of the strategies in the different market environment in the portfolio construction process.

The Problem Statement

Existing research has effectively shown that there is a diversification benefit for the inclusion of hedge funds in a traditional portfolio. However, while research has been conducted to identify the best performing hedge fund strategies in both bull and bear markets, no research has been done on the performance of South African hedge fund styles in different market regimes. Gantz (2013) showed that while global hedge fund strategies did not stay true to the tin during the global financial crises, losing value along with other asset classes, South African hedge fund strategies painted a different picture. While during the bull period, the equity market outperformed South African hedge fund indices, the hedge fund indices showed that investors in hedge funds were protected from the significant capital loss exhibited by the equity market indices during the global financial crises.

Questions have been raised over the diversification benefit offered by hedge funds in recent periods. Equity markets have produced strong returns post the global financial crisis, following the injection of liquidity by most Central Banks into the financial system. In this environment, hedge funds have lagged traditional asset classes. This study seeks to develop an optimisation framework taking into consideration the performance of South African hedge fund indices and the South African economic environment.

Objectives of the study

The specific objectives of this study are to:

1. Examine the performance of hedge funds strategies under different market conditions.
2. Develop a portfolio construction framework for the fund of hedge fund industry in South Africa

Significance of the study

Due to the South African market still being in its infancy in comparison to its global counterpart, there is limited research available on the South African hedge fund domain. This research will add to existing literature by filling the knowledge gap that exists in the South African hedge fund industry. In particular, the hedge fund strategies that dominate the South African landscape will be analysed to determine how these strategies have performed in different market regimes. This research will focus on markets and economic factors specific to South Africa.

Based on the characteristics of the hedge funds in South Africa, an appropriate portfolio construction framework will be investigated. As part of this framework, this study will attempt to determine the optimal number of funds in a portfolio of hedge funds.

This study will be of particular interest to both local and global investors who are active or considering investing with South African hedge funds, as this research will provide insight into the behaviour of the South African strategies.

Literature Review

Authors	Year	Geography	Findings
Baccman, Jean-François. Scholz, Stefan	2003	Global	Due to the asymmetric nature of the distribution, analysis of hedge funds based solely on mean and variance cannot convey the entire risk profile of hedge funds. Using solely mean

			and variance will result in suboptimal decisions with respect to performance measurement and portfolio construction.
Géhin, Walter. Vaissié, Mathieu	2004	Global	The inefficiency of using traditional performance measures to account for hedge fund risks resulted in a proliferation of multi-factor models in an attempt to measure hedge fund alpha. However, most often traditional multi-factor models were adapted to hedge funds, and fail to appropriately account for the specific characteristics of hedge funds, specifically the dynamic and non-linear exposures to the risk factors.
Capocci, Daniel. Corhay, Albert. Hubner, Georges	2003	Global	Hedge funds significantly outperformed through a complete market cycle, with the bullish cycle contributing significantly to returns, but no significant underperformance over the bear market cycle was reported.

Heidorn, Thomas. Kaiser, Dieter. Lucke Daniel	2012	Global	The finding of the study showed that the strategies were favourable for all basic asset classes in bull markets, and on government bonds during bear markets. This supports the integration of hedge funds into a traditional portfolio construct as hedge funds can change their exposures from bull to bear phases by substituting within the basic asset classes.
Sun, Zheng. Wang, Ashley W. Zheng, Lu.	2014	Global	Hedge funds exhibit persistence in performance in periods following relative market weakness, but the same cannot be said following periods of relative market strength. The study linked hedge fund performance persistence to variation of hedge fund market conditions, and finds that the persistence depends critically on the state of the market.
Peskin, Michael W. Urias, Michael	2000	Global	The study found that portfolios with as many as 20 hedge funds typically

S. Anjilvel, Satish I. Boudreau, Bryan E.			preserve the properties of the indices that were used to represent the entire universe. Sharpe ratios were used to assess risk adjusted performance, and it was found that "favourable Sharpe Ratios can be achieved for the median randomly selected portfolio with a modest number of managers.
Amin, Gaurav S. Kat, Harry M	2002	Global	Investigated the performance of baskets of hedge funds ranging in size from 1 to 20. As the number of funds increased, the volatility of the basket declined, but so too did the skewness while the correlation to the equity market increased. The study concluded that combining no more than 15 funds will create a risk-return profile comparable to the population average.
Patel, Kartik	2007	Global	The study finds that a portfolio of approximately 40 funds is appropriate for outperforming the

			benchmark with a high confidence.
Signer, Andreas. Favre, Laurent	2002	Global	Using solely a mean-variance approach tends to show hedge funds as having superior risk-adjusted returns than would be the case if the higher moments were taken into account. This results in a risk of over-allocation to these strategies. To ascertain the true nature of the investments, the skewness and kurtosis of the blended portfolio of traditional and hedge fund investments need to be taken into account.
Giamouridis, Daniel. Vrontos, Ioannis D	2007	Global	This study considered the impact of modelling dynamic covariance and correlations of hedge fund returns on the optimal portfolio construction, to determine if an optimal tactical style allocation method can be achieved.
Bruder, Benjamin. Darolles, Serge	2007	Global	The findings show correlation dynamics to be the main feature that

			needs to be integrated into fund of hedge fund portfolio construction.
Favre, Laurent. Galeano, José-Antonio	2002	Global	To take into account the higher moments of the distribution, this study constructed a measure called modified Value-at-risk which modified the traditional Value-at-risk methodology to include volatility, skewness and kurtosis. Financial assets that have a negative skewness and positive excess kurtosis will exhibit a higher modified VaR than the normal VaR measure.
Darolles, Serge. Vaissié, Mathieu	2014	Global	This study considered the dynamics of the variance and correlations and found that if properly accounted for, the downside risk can be mitigated without compromising on the excess returns.

Overview of Methodology

In considering the performance of the different South African hedge fund strategies in the various market regimes, the time period under consideration will be the period from January 2007 to December 2013. The following model will be used to analyse the performance of each of hedge fund style in relation to a traditional market environment:

$$\boldsymbol{R} = \boldsymbol{\iota}'\boldsymbol{\alpha} + \boldsymbol{\beta X} + \boldsymbol{\gamma} D_1 + \boldsymbol{\delta} D_2 + \boldsymbol{\varepsilon}$$

Where:

R is an n-vector of returns associated with hedge fund strategy indices

α is the n-vector return generated that is independent of the market factors defined by vector X

ι is an n-vector of ones

β is an $(n \times k)$ matrix of sensitivities of the strategy indexes to factors corresponding to market conditions, X

X is a k-vector of factors corresponding to various market conditions

D_1 is a dummy variable that takes a value of "1" in a recession and "0" during non-recession periods

D_2 is a dummy variable that takes a value of "1" when there are expectations of rising interest rates and "0" elsewhere, as discussed below

γ, δ are an n-vectors of sensitivities to the dummy variables

ε is the vector of error terms

The factors considered are as follows:

i. The performance of the JSE All Share Index.

ii. The expectation of rising or falling interest rates as measured by the change in the Forward Rate Agreement (FRA) yield curve.

iii. A proxy for South African economic growth. The official Gross Domestic Product (GDP) figure that is published will not be suitable for this analysis as it is produced on a quarterly basis, and this research will be conducted on a monthly frequency. Therefore, local manufacturing production will be used as a proxy for South African growth. This was considered a suitable proxy as it is a monthly produced index, and has a correlation of 0.75 with GDP over the period under consideration.

iv. A dummy variable will be used to assess the performance of the strategies in an equity bear market. The dummy variable will be assigned a value of one from the period Jan 2007 to Dec 2009 as this corresponds to the bear market associated with the Global Financial Crisis, and takes a value of zero thereafter corresponding to the bull market that characterised the recovery.

v. A second dummy variable will be used to analyse the performance of the strategies in an environment where there is an expectation of rising interest rates. This is defined as a period where the difference between the 9x12 Forward Rate Agreement and the 1x4 Forward Rate Agreement is positive. In these periods, the dummy variable will be set as 1, or take a value of 0 otherwise.

The rationale for including these variables has been discussed in detail in the Research Methodology chapter (page 38).

The outcome of the analysis conducted on the South African hedge fund styles will then be used to consider a framework for construction of a portfolio of hedge funds.

Currently, the classical mean-variance optimisation framework is commonly used but this tends to under-represent the risk due to the non-normal distributions characteristic of hedge funds (Signer and Favre (2002), Lamm (2003) and Davies, Kat and Lu (2004)). As part of the portfolio construction process, an examination of the optimal number of funds in a portfolio of hedge funds will also be conducted. Global research has shown when pooled together, a portfolio of assets that have a low correlation with each other will result in a lower volatility of the pooled assets. However, the cost of this lower volatility is usually lower return. Findings on the number of funds in a fund of hedge fund at which the risk reduction benefit diminishes is inconclusive across global strategies as highlighted in the literature review summary on pages 8 – 13. No similar research currently exists for local strategies. The technique of random sampling from the complete universe of hedge funds will be used to generate portfolios. The risk return characteristics of these portfolios will be calculated to determine the effect of inclusion of each additional fund in the portfolio. The skewness and kurtosis of each portfolio will also be taken into account in the analysis to assess the impact of increasing the number of funds on the higher moments.

Data and Data Collection

All empirical analysis conducted in this research is based on secondary data sources. Hedge funds typically publish monthly returns which means it can take years to collect a meaningful number of data points. The number of funds and strategies available in the South African market with long histories is limited and using individual fund data will result in the estimation risk being exacerbated. To address this issue, this study uses publicly available hedge fund strategy indices. South African hedge fund indices will be sourced from HedgeNews Africa.

HedgeNews Africa is a South African hedge fund publication that collates hedge fund return information from the broader South African participants. HedgeNews Africa hosts a comprehensive database of funds investing in South Africa, and constructs indices for the following broad strategy classifications: equity long short, fixed income arbitrage, equity market neutral and quantitative strategies, and multi-strategy. Data is compiled and reported monthly and is available since January 2007 from this provider.

Market indices and economic data will be sourced from both i-Net and Bloomberg.

Chapter 2: Literature Review

Total assets under management for the hedge fund industry globally reached an all-time high of USD 2.6 trillion in 2013. Assets are invested across over 10 global hedge fund strategies in a mature industry. Extensive research has been conducted on the global hedge fund industry as the interest in alternative investments has skyrocketed, with alternative investments growing at a faster rate than traditional investments and surpassing the assets under management reached prior to the global financial crisis as investors seek more esoteric strategies to diversify their portfolios post the crisis. Research has spanned across a range of fields including an analysis of the characteristics of global hedge fund strategies, measuring hedge fund performance and persistence, identifying appropriate risk factors and constructing optimal hedge fund and fund of hedge fund portfolios (Cazalet and Zheng, 2014).

The subsequent literature review provides an overview of the hedge fund investment, and stylised characteristics of hedge funds. It goes on to detail the research available of performance persistence across hedge fund strategies, and different considerations for the portfolio construction of fund of hedge funds – one of the main avenues for accessing hedge fund exposure.

Hedge fund overview

A hedge fund is a private, pooled investment vehicle that invests in a variety of securities and tends to target an absolute return profile. This means that it aims to achieve positive returns regardless of whether the market is rising or falling. This is accomplished by the hedge funds ability to take both long and short positions in

securities — as the name “hedge” fund implies — which, in principle, enables investors to be able to profit from both positive and negative movements while maintaining little directional exposure to the market (Lo, 2008). As Phillips (2006) points out, the degree of directional exposure (“risk hedging”) depends on the strategy. Phillips classifies hedge funds into two broad categories: non-directional and opportunistic. Non-directional strategies look to isolate the idiosyncratic risks of the underlying securities while neutralising broad market exposure compared to opportunistic strategies that take active directional bets. These investments are sought after for the prospect of potentially higher returns than those available from investments in traditional asset classes through their ability. to profit from both rising and falling markets. Hedge funds can invest across a range of markets and employ a variety of investment strategies and securities. Two of the most common strategies unique in hedge fund execution are, firstly the use of leverage, and second the ability to short sell. Barabarino (2007) defines leverage as ‘the level of gross assets greater than equity capital invested’. Leverage is used to magnify the return, and consequently the risk, of the original equity investment. Simply, leverage can be defined as the sum of the absolute long exposure and the absolute short exposure. Short selling is a trading strategy that seeks to capitalise on the anticipated decline in the price of a security.

Stylised characteristics of hedge funds

It is well documented that hedge fund returns are not normally distributed, tend to exhibit high levels of skewness (either positive or negative) and high kurtosis. Skewness, the third moment of a distribution, is a measure of the degree of asymmetry of a distribution around its mean. A distribution that is characterised by

positive skewness displays an asymmetric tail extending toward more positive values, while a negatively skewed distribution displays an asymmetric tail towards more negative values. Kurtosis, the fourth moment of a distribution, is a measure of the relative peakedness or flatness of a distribution compared with the normal distribution. Kurtosis is measured relative to that of a normal distribution which exhibits a kurtosis of 3. A higher value indicates a distribution more peaked than a normal distribution, while a lower value is indicative of a flatter distribution (Ranaldo and Favre, 2005). These characteristics are a consequence of the non-traditional trading strategies, such as the use of leverage and derivatives, that are employed by hedge funds. These trading strategies can cause disproportionate (or non-linear) returns versus the underlying asset class returns and this may impact on the interpretation of the mean and variance of the distribution (Bacmann and Gawron, 2004; Phillips 2006).

The inclusion of hedge funds into a portfolio of traditional investments therefore has strong implications for the risk-return profile of the resulting portfolio. This is due to the risks relating to traditional investments being different to those of hedge funds. Bacmann and Scholz (2003) describe the risk drivers of traditional investments to be more “linear in their performance impact” and directly relate to the underlying markets. This is in contrast to the risks associated with hedge funds which are more complex in that they are non-linear and usually not well understood. The implication is that performance measures, such as standard deviation and Sharpe ratio, are not adequate to quantify risk and performance. Bacman et al found that the inclusion of hedge funds in traditional portfolios enhanced the overall return profile, while reducing the standard deviation. However, when skewness is taken into account the

results are not as favourable. Bacman et al concludes that the risk of portfolios containing hedge funds can therefore not be assessed by looking at volatility only, or at higher moments individually.

Performance persistence in hedge funds

Due to the asymmetric nature of the distribution, analysis of hedge funds based solely on mean and variance cannot convey the entire risk profile of hedge funds, as any mean-variance calculation evaluates the deviations above and below the mean equally, rather than assigning more weight to the likelihood of large deviation to the downside. This may lead to suboptimal decisions with respect to performance measurement and portfolio construction. (Phillips 2006, Baccman and Scholz (2003)

Peskin, Urias, Anjilvel and Boudreau(2000) and Schneewies, Kazemi an Szado (2012) found the distribution of realised performance among individual hedge funds to be wide. This finding is true when considering returns within strategies, as well as between strategies. Peskin et al attributes this wide dispersion in returns to the range of techniques employed by hedge funds to generate returns.

Gehin and Vaissie (2004) agreed with Bacman et al (2003) that traditional performance measures do not appropriately account for hedge fund risks. This explains the proliferation of the use of multi-factor models in an attempt to measure hedge fund alphas. A factor model aims to identify the relationship between the returns for a particular return series and a list of variables that likely impact a fund's returns. However, most often traditional multi-factor models were adapted to hedge funds, and also fail to properly account for the specific characteristics of hedge funds, specifically the dynamic and non-linear exposures to the risk factors (Gehin and Vaissie, 2004).

Fung, Hsieh, Naik and Ramadorai (2008), Schneewies, Kazemi and Szado (2012) and Capocci, Corhay and Hubner (2003) used different variations of multi-factor models to analyse hedge fund returns, and found that a large variation in hedge fund returns can be explained by their exposure to various macro risk factors. Jagannathan, Malakhov and Novikov (2010) and Gehin and Vaissie (2004) reported contradictory findings to this, finding that standard factors fail to explain the returns produced by hedge fund returns. Further to this, Jagannathan et al found that due to the illiquid nature of some of the assets held by hedge funds, the returns tend to exhibit substantial serial correlation, which if not accounted for, can bias the performance measurement used.

Sandvik, Fryedenberg, Westgaard and Heitman (2011), Capocci, Corhay and Hubner (2003) and Edwards and Caglayan (2000) studied the performance of hedge fund strategies in bull and bear markets, and found that hedge funds created superior risk adjusted returns in bull periods but lacked evidence to support any superior performance in bear markets. Sandvik et al found that despite the hedge fund composite failing to create abnormal returns, more than half of the sub-strategies displayed significant alpha. While Cappocci et al, considered hedge fund strategies only, Edwards et al included both hedge fund strategies and commodity styles in their analysis under the broad categorisation of alternative investments. Capocci et al (2003) and Edwards et al (2000) both found the market neutral strategy to produce the most persistent results from all the strategies, throughout the cycle. Sandvik et al (2011) found that only one strategy that exhibited significant alpha during the bear markets was the global macro strategy. Edwards et al (2000) concluded that the market neutral, event driven and global macro strategies provide a more attractive return profile over the complete market cycle than do the

commodity funds. This he attributed to these strategies offering relatively good downside protection in stressed markets. However, hedge funds appeared to have a higher positive correlation with equities in bear markets than bull markets. This contradicts the diversification benefit that investors are seeking. (Edwards et al (2000)) Capocci et al (2003) found hedge funds significantly outperformed through a complete market cycle, with the bullish cycle contributing significantly to returns, but no significant underperformance over the bear market cycle was reported. Brown, Gregoriou and Pascalau (2011) explains the larger positive correlations during bear markets to be attributable to the liquidity risk that hedge funds are inherently exposed to, and investors should therefore not expect these investments to perform well in liquidity crises.

Heidorn, Kaiser and Lucke (2012) extended the research to include the betas of different hedge fund strategies on more basic asset classes in different market environments. The study considers basic asset classes as equities, bond and commodities, all of which are investments within hedge funds. Heidorn et al (2012) considered the global hedge fund universe and divided the universe into the equity market neutral, relative value, event driven, global macro and managed futures styles. The finding of the study showed that the strategies were favourable for all asset classes in bull markets, and on government bonds during bear markets. This supports the integration of hedge funds into a traditional portfolio construct as hedge funds can change their exposures from bull to bear phases by substituting within the basic asset classes.

Agarwal and Naik (2000) extended the standard two-period bull-bear market analysis to include a multi-period framework to determine if performance persistence exists in hedge funds. This is done by analysing the wins and losses over multiple

consecutive time intervals, in particular looking at quarterly, half-yearly and annual intervals. In a multi-period framework, the likelihood of observing persistence by chance is lower than in the traditional two-period framework. Persistence is weakest at the yearly horizon, while being highest at the quarterly horizon. Hedge fund strategies globally can by subject to liquidity constraints and long lock-up periods, which make it difficult to take advantage of this shorter persistence. When considering the multi-period framework, persistence is considerably smaller than the two-period comparison. This was irrespective of whether the fund followed a directional or non-directional strategy.

Sun, Wang and Zheng (2014) found that hedge funds exhibit persistence in performance in periods following relative market weakness, but the same cannot be said following periods of relative market strength. The study measured the relative performance of individual funds to the hedge fund aggregate in both positive and negative periods. Funds that performed better in the negative periods significantly outperform their peers over the following 3 months to two years. This is indicative of performance in market weakness being more informative about fund manager skill, and therefore more replicable into the future. Sun et al link hedge fund performance persistence to variation of hedge fund market conditions, and finds that the persistence depends critically on the state of the market.

Carlson and Steinman (2008) studied hedge fund failures specifically and looked at a range of market factors to determine whether they are associated with hedge fund failures. The study focussed primarily on the US markets, and hedge fund failures were regressed on a variety of market returns, spreads and realised volatility measures as well as hedge fund characteristics. The finding of the study was that

market conditions do affect the likelihood that a hedge fund meets the desired return objective of investors. Secondly, the study showed the hedge fund industry to be fairly robust in various stressed environments such as sharp asset price movements similar to August 1998, a multi-standard deviation fall in the S&P500 equity market, or a multi-standard deviation fall in the value of the dollar.

The literature confirms that hedge funds tend to exhibit high levels of both skewness and kurtosis. Therefore, traditional risk measures such as standard deviation and Sharpe ratios do not adequately capture the risk of these funds. This explains why traditional multi-factor models adapted to hedge funds fail to properly account for the hedge fund risk profile. Findings regarding performance in different market environments differ depending on the hedge fund indices used and the markets considered. This confirms that global research cannot be easily adapted to the South African context, and further analysis on the South African hedge fund strategies is required.

Gaining access to hedge fund exposure

Investors have two main avenues to gain access to hedge fund exposure. The first being direct investment in hedge funds and the second is via a fund of hedge funds. A fund of hedge funds is a hedge fund that invests in other hedge funds. Brown et al (2011) reported that over the prior decade nearly every financial institution has increased their exposure to alternative investments through fund of hedge funds.

Fund of hedge funds add an additional layer of fees to what is already a high fee investment. However, this added layer of fees is in exchange for active risk management and monitoring. The added trading strategies and flexibility in the mandate means that more monitoring and analysis is required, and this can be

cumbersome for an investor who considers a direct investment. The fund-of-hedge-fund specialists have sufficient expertise and experience of the range of complex strategies (Jones, 2007).

The diversification of investing through a fund of hedge funds is an added benefit. Fund of funds should construct superior diversified portfolios to a basic diversification due to the fund of funds specialist having added insight into the nature and cyclicality of the different hedge fund strategies (Jones, 2007).

Ang, Kropf and Zhao (2005) studied the benefit of accessing hedge funds via direct exposure versus access via a fund of hedge funds. Their finding showed that the evaluation of fund of hedge funds versus accessing hedge funds directly differ for every investor. There is a wide dispersion in returns across hedge fund strategies and individual funds. New investors to the industry are more likely to choose an incompetent manager and pay a large penalty for this. When pooled together, the risk of a portfolio of hedge funds is dramatically lower in a well-constructed portfolio due to the low correlations between individual hedge fund strategies (Peskin et al). Investors with more experience and a low cost structure prefer to invest directly in hedge funds as they are able to better assess the hedge fund strategies and construct diversified portfolios. Preqin[4] agreed with this finding that new investors to the industry tend to invest via fund of hedge funds, but switch to direct investments as they gain more knowledge of the industry.

Preqin reported a decline in global fund of hedge fund assets over 2013, as investors moved towards direct investing as they tried to gain greater control over their fund of hedge fund assets. Of those investors now directly accessing hedge fund exposure,

[4] Preqin is a leading source of data and intelligence for the global alternative investment industry. Website: https://www.preqin.com/

63% had previously invested through funds of hedge funds, highlighting that the majority of these investors have changed their investment style since they first began investing in the asset class. Most investors cited the double layer of fees as the main reason for moving away from fund of hedge fund strategy.

Portfolio Construction: Finding the Optimal number of managers

Since Markowitz (1952), portfolio diversification has been a traditional way of reducing risk. When pooled together, a portfolio of assets that have a low correlation with each other will result in a lower volatility of the pooled assets. However, the cost of this lower volatility is usually lower return. When looking at a fund of hedge fund construct, Brown et al (2011) suggests that the larger the number of underlying funds in the fund of hedge fund portfolio, the more exposed it will be to negative market conditions. The risk reduction benefit appears to diminish as the number of funds in the fund of hedge fund reaches between 10 and 20 underlying funds. Having too many funds in the portfolio, results in loss of meaningful risk reduction, leads to lower returns and in extreme cases, where the cost of operational due diligence is considerable, can result in the end of the fund when it becomes too expensive to perform necessary due diligence and monitoring. (Brown, 2011; Patel, 2007)

Peskin et al (2000), Amin and Kat (2002), Patel (2007) and Amo, Harasty and Hillion (2007) were among a few to investigate the optimal the optimal number of funds to be included in a fund of hedge fund. Amo, Harasty and Hillion (2007) conducted the analysis through simulation exercises that involved constructing randomly selected portfolios from a fixed database of global hedge funds. The risk and return characteristics were then calculated for each of the constructed portfolios. Peskin et al (2000) conducted the research to determine if the summary statistics of hedge

fund indices are appropriate. Their concern was whether the performance and risk characteristics represented by the indices can be achieved in actual portfolios of a more realistic size. Peskin et al (2000) found that portfolios with as many as 20 hedge funds typically preserve the properties of the indices that were used to represent the entire universe. The one caveat is that the constructed portfolios do not reflect the cost of building these portfolios. Sharpe ratios were used to assess risk adjusted performance, and it was found that "favourable Sharpe Ratios can be achieved for the median randomly selected portfolio with a modest number of managers."

Amin and Kat (2002) investigated the performance of baskets of hedge funds ranging in size from 1 to 20. As the number of funds increased, the volatility of the basket declined, but so too did the skewness while the correlation to the equity market increased. The changes were most significant for the smaller baskets, while holding more than 15 funds changed very little. Amin and Kat (2002) concluded that combining no more than 15 funds will create a risk-return profile comparable to the population average.

Both Patel (2007) and Lhabitant and Learned De Piante Vicin (2004) considered both a naïve strategy and a "smart" strategy in their simulations. Naïve diversification randomly selects the fund from the universe under consideration and the strategy of the fund is ignored, and strategy diversification whereby the number of funds that are drawn per strategy are constrained. Patel uses the fund managers included in the Credit Suisse / Tremont hedge fund index[5] as the universe for his fund selection. While a naïve diversification approach is adequate for a diversified fund of hedge

[5] The Credit Suisse / Tremont hedge fund index is the largest asset weighted global hedge fund index.

fund comparison, the strategy diversification approach is more appropriate for strategy specific fund of hedge funds. Patel finds that a portfolio of approximately 40 funds is appropriate for outperforming the benchmark with a high degree of confidence. Conversely, Lhabitant et al (2004) finds that approximately 10 hedge funds are sufficient to eliminate most of the portfolio risk, and including more than 10 funds in the portfolio is likely to result in “diworsification”.

Amo et al (2007) studied the risk reduction as the number of funds increased from 1 to 25 in a fund of hedge funds. The study found that the risk of the portfolio roughly halves when holding six funds or less. For portfolios of greater than six funds, the marginal risk reduction is less than 5% over the different holding periods. This study also finds that fund of funds are more heterogeneous than their value proposition and are not as diversified as they should be.

The reviewed literature provides no definitive answer for the number of funds to be included in a fund of fund portfolio with the results varying depending on the strategies, the geographic focus and environments. Studies have focussed on global strategies with no research available for the South African environment.

Fund of Hedge Fund portfolio construction techniques

Research in hedge fund investing proposes different solutions to build optimal hedge fund portfolios. While Markowitz’ mean-variance approach has been the subject of much criticism when considering the non-normal nature of hedge fund return distributions, much of the existing research has been conducted in the framework of normal and identically distributed returns. Using solely a mean-variance approach tends to show hedge funds as having superior risk-adjusted returns than would be

the case if the higher moments were taken into account. This results in a risk of over-allocation to these strategies. To ascertain the true nature of the investments, the skewness and kurtosis of the blended portfolio of traditional and hedge fund investments need to be taken into account. (Signer and Favre 2002, Lamm 2003)

Favre and Galeano (2002), Bruder and Darolles (2007), Giamouridis and Vrontos (2007), Davies, Kat and Lu (2004) and Darolles and Viassie (2014) were among the few that factored in the non-normal distribution properties into their portfolio construction analysis. Giamouridis et al (2007) considered the impact of modelling dynamic covariance and correlations of hedge fund returns on the optimal portfolio construction to determine if an optimal tactical style allocation method can be achieved. By using time varying covariance and correlation, the portfolios constructed exhibited a better risk adjusted profile through dramatically reducing the peak to trough drawdowns during market stress and still being able to participate in the market recovery. The allocations determined by the dynamic models were significantly different to other models available at the time. Bruder et al (2007) further analysed the dynamic correlation models and found these models resulted in better performing hedge fund portfolios with better diversification. Bruder et al (2007) finds correlation dynamics to be the main feature that needs to be integrated into fund of hedge fund portfolio construction. Bruder et al (2007) also considered extensions to the mean-variance models, but found that these extensions to be lacking in producing better performing portfolios of hedge funds. Davies et al (2004) also attempted to solve for the optimal portfolio construction within a mean-variance-skewness-kurtosis framework. This study found that introducing the higher moments into the portfolio optimisation process yields portfolios significantly different to the

classic mean-variance optimal portfolio with much less attractive mean-variance characteristics. This study also showed that while certain hedge fund strategies were favoured in the portfolio decision making process (and others completely discounted), hedge funds and stocks did not combine well with equities in terms of skewness.

Favre and Galeano (2002) construct a measure called modified Value-at-risk which adapted the traditional Value-at-risk methodology to include volatility, skewness and kurtosis. Financial assets that have a negative skewness and positive excess kurtosis will exhibit a higher modified VaR than the normal VaR measure. A portfolio can therefore be constructed to have the lowest probability of losing more than the modified VaR at a defined confidence level (Favre and Galeano, 2002).

Dallores and Viassie (2014) also considered the dynamics of the variance and correlations and found that if properly accounted for, the downside risk can be mitigated without compromising on the excess returns. However, the implementation of this type of tactical allocation strategy is not practically possible over the long term as this requires that the investor be able to act on the information very quickly, and at a negligible cost. To address the issue of not being able to rapidly implement this type of tactical allocation, Darolles and Viassie (2014) suggests including a structurally long volatility exposure in the portfolio that will diversify the portfolio and smooth the risk profile of the overall allocation. A second alternative is to combine the historical probabilities of the various market regimes with the investors' expectation of the near-term regime to transition the portfolio towards the appropriate style. This will reduce the costs associated with a rapid reallocation of the portfolio.

The third alternative suggested is to utilise an overlay solution such that a systematic hedging strategy using very liquid investments is used to "bridge the gap" of the illiquidity costs of the underlying assets.

Phederson (2013) developed a portfolio construction framework which decomposed hedge fund returns into an alpha component and a beta component, where the beta return was derived from traditional risk factors. The framework looks to identify those funds that exhibit a statistically significant alpha over time with limited beta exposure. A quantitative ranking methodology is implemented to complement the qualitative manager selection process.

The reviewed literature shows consensus that the classical mean-variance approach is insufficient for the non-normal nature of the typical hedge fund return distribution. The portfolio construction models employed to cater for this are varied with emphasis placed on a range of different metrics such as VaR, covariance, correlation and alpha analysis. All reported analysis has been done on the global hedge fund indices, but no similar studies exist for the South African hedge fund industry.

The South African hedge fund landscape

The South African market is still in its infancy relative to its global counterpart and research of the local industry remains limited. While the first hedge fund was developed in the US in 1949, the South African scrip lending market only became mature enough to facilitate short selling in the 1990's. The market was initially characterised by niche players catering for specific investors, but by the early 2000's approximately 28 hedge funds were operating in the South African market – albeit

predominantly following the equity long short strategy. 2013 (AIMA, South Africa[6]). HedgeNews Africa[7] reported assets under management of South African strategies to have reached an all-time high of R52.03bn at the end of December. South African fund of funds remain the largest allocators to the hedge fund industry, accounting for 63% of rand denominated assets. However, many of the fund managers do not yet have track records long enough to be considered by institutional investors. The latest industry survey produced by Novare Investments[8] showed that 78.5% of the industry assets can be accounted for by the equity long short, equity market neutral and fixed income arbitrage strategies, with equity long short remaining the dominant strategy accounting for 52.5% of total industry assets.

The equity long short strategy takes long positions in stocks that are expected to appreciate in value, and takes short positions in stocks that are expected to decrease in value. The short positions allow the strategy to minimise exposure to the market, and profit from a change in the spread between the long and short positions. Equity long short strategies tend to exhibit a higher degree of correlation to the market than other equity strategies due to long positions typically being larger than the short positions. The short positions provide a hedge to the overall long portfolio and as a result the equity long short strategies typically lag equity indices in strong bull markets, but will outperform the broad market in a bear market[9].

[6] AIMA South Africa is the South African chapter of the Alternative Investment Management Association.
[7] HedgeNews Africa is a South African based hedge fund publication. The online publication can be accessed at http://www.hedgenewsafrica.com
[8] Novare Investments is a South African based asset manager who compiles and publishes an annual report on the South African landscape. Latest survey available at http://www.novare.com/uploads/files/SAHedgeFundSurvey2.pdf

[9] http://www.barclayhedge.com/research/educational-articles/hedge-fund-strategy-definition/hedge-fund-strategy-equity-long-short.html

An equity long short strategy that executes the long and short strategies such that long exposure is approximately equal to the short exposure is called an equity market neutral strategy. The equity market neutral strategy will take long positions in a company and short sell shares in a similar company such that the economic factors that affect prices in both companies are offset and the active bet is on company-specific factors. In this way, the strategy is agnostic to market direction.[10]

Fixed-income arbitrage hedge funds also exploit price discrepancies in the fixed-income market, including bonds, forward rate agreements (FRAs), swaps and other debt instruments. Fixed-income arbitrage funds will take both a long and short position in two similar fixed-income securities, such that the long short spread is expected to revert to a fair value. The fair value can be determined from a macroeconomic perspective, or through quantitative valuation techniques. A common strategy within the fixed income arbitrage discipline is yield curve arbitrage. The yield curve is a graphical representation of the yields of fixed income instruments of different maturities. Fund managers can take long and short positions in instruments of various maturities in an attempt to profit from mispricings in securities or from shifts along the yield curve. [11]

Multi-strategy hedge funds invest across a range of hedge fund strategies, asset classes and geographical regions. The value proposition of this type of strategy lies

[10] http://www.barclayhedge.com/research/educational-articles/hedge-fund-strategy-definition/hedge-fund-market-neutral.html

[11] http://www.barclayhedge.com/research/educational-articles/hedge-fund-strategy-definition/hedge-fund-strategy-fixed-income.html

in the fund manager's ability to allocate capital dynamically and efficiently across the various hedge fund strategies dependent on the current market opportunities. [12]

Quantitative strategies also have a place in the South African market, but are limited in both number of funds and the assets under management. These strategies use purely quantitative techniques to assess the behaviour of shares or indices, and look to profit based on signals generated from quantitative or statistical signals. The most common of these is the trend following and statistical arbitrage strategies. Trend following systematic strategies make use of computer programmes identify trends and capture large directional moves different markets.[13] Statistical arbitrage strategies use statistical techniques to identify statistical mispricings in stocks based on their long term behaviour with similar stocks.[14]

The number of strategies available in the South African environment is far fewer than are available in the global arena. The reviewed literature shows that many global studies have been conducted to further understand the performance of the difference hedge fund strategies under different market conditions. These studies span various global indices and locations but do not take into account the South African hedge fund strategies or market environment. This research will leverage off the studies from global research to apply to the South African environment.

[12] http://www.barclayhedge.com/research/indices/ghs/Multi_Strategy_Index.html

[13] http://www.morningstar.co.uk/uk/news/69379/commodity-trading-advisors-%28cta%29-explained.aspx

[14] http://www.hedgefund-index.com/d_statarb.asp

Chapter 3: Research Methodology

This research sets out to firstly examine the performance of the South African hedge fund strategies under different market environments, and secondly, to investigate a portfolio construction framework for a fund of hedge fund in South Africa.

Part 1

In considering the performance of the different South African hedge fund strategies in the various market regimes, the time period under consideration will be the period from January 2007 to December 2013. The period was selected firstly due to the availability of index data from the HedgeNews Africa data provider, and secondly as this period encompasses both a significant equity market correction viz. the Global Financial Crisis, as well as the strong equity bull market that has followed.

The following model will be used to analyse the performance of each of hedge fund style in relation to a traditional market environment:

$$\boldsymbol{R} = \boldsymbol{\iota}'\boldsymbol{\alpha} + \boldsymbol{\beta}'\boldsymbol{X} + \boldsymbol{\gamma}D_1 + \boldsymbol{\delta}D_2 + \boldsymbol{\varepsilon}$$

Where:

R is an n-vector of returns associated with hedge fund strategy indices

α is the n-vector return generated that is independent of the market factors defined by vector X

ι is an n-vector of ones

β is an $(n \times k)$ matrix of sensitivities of the strategy indexes to factors corresponding to market conditions, X

X is a k-vector of factors corresponding to various market conditions.

D_1 is a dummy variable that takes a value of “1” in a recession and “0” during non-recession periods

D_2 is a dummy variable that takes a value of “1” when there are expectations of rising interest rates and “0” elsewhere, as discussed below.

γ, δ are an n-vectors of sensitivities to the Dummy variables

ε is the vector of error terms

The factors are considered:

i. The performance of the JSE All Share Index: Following the credit crisis of 2008 which saw the S&P 500 index drawdown in excess of 50%, investors have been seeking alternative ways to manage their equity portfolios that allows the benefit of stock selection, but with a much lower volatility and drawdown risk than that which has become the hallmark of the market. Equity long short funds seek to produce equity-like returns with lower volatility compared to long-only equity strategies (Hart et al, 2014). One of the most common questions asked when assessing equity long short strategies is what level of equity market beta does the fund manager target. The higher the beta for a portfolio, the more dependent it is to a rising market; and consequently, the more exposed it will be to market declines. The JSE All Share Index was selected as a factor for consideration in this model as it is the broad South African equity index, and can be used to determine if the equity centric hedge fund strategies are deriving a significant portion of the returns through exposure to equities rather than hedging strategies (Altegris, 2012; Causeway, 2014).

ii. The expectation of rising or falling interest rates as measured by the change in the Forward Rate Agreement (FRA) yield curve. A FRA is a 3 month agreement to exchange a fixed rate for a floating rate for a period of time over the next 24 months. The floating rate represents the markets expectation for interest rates over the period of the agreement. When the floating rates for these agreements are charted together, the result is the Forward Rate Agreement curve (or yield curve) and represents the expectation for interest rates of market participants over the period. Where the longer dated FRAs have a higher floating rate than the shorter dated FRAs, the market expectations is one of rising interest rates. Conversely, if the shorter dated FRAs have a higher rate than the longer dated FRAs, the market expectation is one of falling interest rates over the period. A common strategy in the fixed income arbitrage strategy is to attempt to profit from perceived mispricings in this curve. These perceived mispricings are a function of where the fund managers' view of the level of future interest rates differ to the markets expectations as represented by the yield curve. This is known as yield curve arbitrage. The expectation priced into the FRA is a function of the market participants' technical and economic views, and changes consistently as these views change. This factor considers the daily change in the 12 month segment of the curve to determine if the returns generated by the fixed income arbitrage strategies are affected by the changes in the slope of the curve. (Chua et al, 2004. Leung, 2006).

iii. A proxy for South African economic growth. The official Gross Domestic Product (GDP) figure that is published will not be suitable for this analysis as it

is produced on a quarterly basis, and this research will be conducted on a monthly frequency. Therefore, local manufacturing production will be used as a proxy for South African growth. This was considered a suitable proxy as it is a monthly produced index, and has a correlation of 0.75 with GDP over the period under consideration.

Economic growth impacts on corporate earnings and future earnings expectations. Stock prices are driven by investors' expectations for future corporate earnings, and consequently stock market trends are influenced by growth trends and related cycles (Sandte, 2012). Blanchard (2013) explains that a change in economic growth will cause a commensurate change in average interest rates in an economy, ceteris paribus. This factor was included to determine if the change in economic growth has an impact on the returns of the various hedge fund strategies.

iv. A dummy variable will be used to assess the performance of the strategies in an equity bear market. The dummy variable will be assigned a value of one from the period Jan 2007 to Dec 2009 as this corresponds to the bear market associated with the Global Financial Crisis, and takes a value of zero thereafter corresponding to the bull market that characterised the recovery. These variables are included to determine whether the performance of the hedge funds strategies are more significant in a bear market, similar to the one experienced over the Jan 2007 – Dec 2009 period.

v. A second dummy variable will be used to analyse the performance of the strategies in an environment where there is an expectation of rising interest

rates. This is defined as a period where the difference between the 9x12 Forward Rate Agreement and the 1x4 Forward Rate Agreement is positive. In these periods, the dummy variable will be set as 1, or take a value of 0 otherwise.

Monthly data series were collated for the study. To determine the structure of the dataset to be used, the data was tested for multicolliearity and for heteroskedasticity.

The data was first tested for multicollinearity. Multicollinearity occurs when correlations among the independent variables used in the regression are high, thereby making it difficult to determine which of the independent variables are providing explanatory power for the dependent variable. If there is no relationship between the explanatory variables, they are said to be orthogonal to one another. Table 1 below depicts the pairwise correlation between the explanatory variables used in the study. The correlations between the independent variables are not significant, implying that the data is free from multicollinearity.

Table 1: Correlation of explanatory variables

	JSE All Share	FRA Curve Shape	Manufacturing Production
JSE All Share	1.00		
FRA Curve Shape	0.21	1.00	
Manufacturing Production	0.14	0.20	1.00

The second test performed on the data was one for heteroskedasticity. Heteroskedasticity is said to occur when the variance of the unobservable errors is not constant. Using White's Test for heteroskedasticity, it was concluded that there is

significant evidence of heteroskedasticity, and therefore it is not plausible to assume that the variance of errors is constant in this case.

Due to the presence of heteroskedasticity in the data, the Generalised Method of Moments estimation technique was used. Generalised Method of Moments (GMM) is a semi-parametric estimation method, and has proved to be more robust to model specification than other fully parameterized likelihood-based techniques as it requires less information. GMM brings with it the advantage of consistency in the presence of arbitrary heteroskedasticity (Baum, Shauffer and Stillman, 2003).

The GMM method uses a full set of instrument variables that are expected to be exogenous. Exogenous variables are those that are not systematically affected by changes in the other variables of the model, particularly by changes in the endogenous variables.

The choice of instruments is guided by two key considerations. Firstly, the instrument variable should be correlated with the explanatory variable that it seeks to support and secondly, the instrument must be orthogonal to the error term in the regression. For the explanatory variables under consideration in the model, the monthly percentage change in the price earnings ratio of the JSE All Share Index was used as an instrument for the JSE All Share index. These variables have a correlation of 0.75 over the period of the study. For the ‘Change in Yield Curve Shape’ explanatory variable and the’ Manufacturing Production’ explanatory variable lagged variables were used as instrument variables for these. The ‘Bear Market Dummy’ variable and the ‘Rising Rates Expectation Dummy’ variable were not instrumented due to these being exogenous variables.

Part II

The second part of the study sets out to establish a framework for constructing portfolios of hedge funds. The framework adapts the findings from the analysis conducted on the South African hedge fund styles in Part I. Currently, the classical mean-variance optimisation is commonly used. This can under-represent the risk as it does not take into account the specific risk factors that individual strategies are exposed to, and furthermore does not account for the non-normal distributions characteristic of hedge funds. (Signer and Favre (2002), Lamm (2003) and Davies, Kat and Lu (2004)).

As part of the portfolio construction framework, analysis into the optimal number of funds in a portfolio of hedge funds will also be conducted. Global research has shown that a large number of underlying funds in a fund of hedge fund portfolio can result in the portfolio being over-diversified and there is potential for the portfolio to be more exposed to negative market conditions (Brown, Gregoriou and Pascalau, 2011).

The sample of hedge funds that are included in this analysis are taken from the HedgeNews Africa database. The period under consideration for the study is Jan 2007 to Dec 2013. All hedge funds with a return series spanning the entire 84 month period were included in the sample. The total universe under consideration is therefore 40 hedge funds across the range of South African hedge fund strategies. Figure 2 shows the strategy composition of the hedge fund sample.

Figure 2: Hedge fund universe composition

Strategy of funds	Number	Percentage
Equity long short	15	37.5%
Fixed income arbitrage	12	30.0%
Equity market neutral and quant	9	22.5%
Multi-strategy	4	10.0%

A simple random sampling technique is used to study the effect of varying the number of funds in a portfolio through constructing a series of equally-weighted fund of hedge fund portfolios of increasing size (N = 1, 2 … 40 funds). A portfolio is constructed by randomly selecting N funds from the sample set and equally weighting the constituents. One hundred such portfolios are created for a portfolio of size N to create a distribution for a fund of fund of size N. For each portfolio, a time series of returns was constructed and the annualised return, annualised volatility, skewness and kurtosis are calculated. The 5th, 25th, 50th, 75th and 95th percentiles of each risk and return metric is then computed and used to assess the impact of inclusion of each additional fund on the portfolio of funds. The 5th percentile point is used as a representation of the typical behaviour as it represents the value below which 95% of the observations can be found.

Chapter 4: Empirical Results

Part 1: Analysis of the hedge fund strategies under different market conditions

As per the objectives of the study, the first part of the analysis aims to examine the performance of South African hedge fund strategies under specific market environments. The model defined on page 37 was used for the analysis of the betas to show how the performance of each hedge fund style may develop under each defined market environment.

Using the Generalised Method of Moments estimation procedure, we are able to determine the portion of returns of each of the hedge fund strategy indices that can be attributed to the various market environments as defined by the independent variable viz. the equity market, the shape of the FRA curve, manufacturing production and the dummy variables associated with the equity bear market and an expected rising interest rate market.

The estimation output for each strategy follows. Included in the results is the Durbin Watson statistic. The Durbin Watson statistic tests for autocorrelation in the residuals. This statistic lies between 0 and 4, with a value of 2 implying that there is no autocorrelation in the sample. Values approaching 0 are indicative of positive autocorrelation, while a value tending toward 4 is suggestive of a negative autocorrelation.

i. Equity Long Short

Table 1 below shows the results of the estimation procedure between the equity long short hedge fund style index and the specified market conditions. These results are based on t-testing at a 90% confidence level. A significance (p-value) of lower than

0.10 indicates that the H_0 hypothesis that there exists a strong relationship between the strategy and the independent variables is significant. Consequently, the hypothesis testing that the dependencies expressed by the betas exist, would be accepted. In this case, a dependency exists between the JSE All Share Index (ALSI) and the equity long short strategy index.

Table 1: Estimation output for Equity Long Short strategy index

	Coefficient	Standard Error	t-Statistic	Significance
(constant)	0.006	0.003	1.721	0.089
ALSI	0.215	0.044	4.901	0.000
FRA Curve Shape	1.712	1.522	1.125	0.264
Manufacturing Prod	0.121	0.110	1.094	0.277
ALSI Dummy Var	-0.001	0.003	-0.452	0.653
Rates Expectation Dummy	0.002	0.005	0.467	0.641

R-squared	0.442
Adjusted r-squared	0.406
Durbin Watson Stat	2.088

The contribution of the independent variables to the equity long short strategy index can therefore be shown by:

$$R_{\text{Equity Long Short}} = 0.006 + 0.22X_1 + u$$

Where:

X_1 represents the JSE All Share Index (ALSI)

X_2 represents the FRA curve shape as defined by the difference in the 12x15 FRA and the 1x4 FRA

X_3 represents the Manufacturing Production Index

X_4 represents the dummy variable set to 1 in an equity bear market

X_5 represents the dummy variable set to 1 when short term interest rates are expected to rise

The variance in returns of the independent variables tend to account for 44% of the variability in the returns of the equity long short strategy index over the period Jan 2008 to Dec 2013. The p-values indicate that the JSE All Share Index (ALSI) was the only independent variable that was significant in explaining returns on the equity long short strategy index at the 90% confidence level. The coefficient of 0.22 on the ALSI indicates that when the returns of the ALSI increase by 1%, returns on the equity long short strategy index tend to increase by 0.22% (assuming all other explanatory variables are held constant).

The total return of equity long short strategies compromises of the return generated from market exposure (net exposure), and that return generated through stock selection or market timing. Net exposure is defined as the total long exposure less the total short exposure and represents the effective exposure to the broad market.[15] Net exposure defines the extent and direction to which the fund will participate in the ALSI movements. South African equity long-short funds have exhibited an average

[15] advisor.morningstar.com/uploaded/pdf/Alt_Long-ShortEquity.pdf

net exposure of between 40% and 100% over the period (Novare Investments Survey, 2013). The tendency of these funds to be long biased (i.e. have positive equity market exposure) denotes that the fund will participate in the same direction as the ALSI, and with a magnitude of between 40% and 100% of the moves experienced by the ALSI. This explains why the ALSI is significant in explaining returns of the strategy. The coefficient of 0.22 on the ALSI indicates that when the returns of the ALSI increase by 1%, returns on the equity long short strategy index tend to increase by 0.22% (assuming all other explanatory variables are held constant). This compares more favourably to global indices. The HFRI Equity Hedge Index, a global hedge fund index frequently cited as a proxy for equity long short hedge fund performance has exhibited a beta of between 0.56 and 0.66 to the MSCI world over time.[16]

The other factors specified in the model are not significant in explaining the equity long short strategy returns. Selbovitz and Joffe (2013) explain that equity long short mandates are not directly impacted by changes in interest rates or increased economic growth. In an environment of increased economic growth, price levels are expected to increase as real output grows Equity markets are forward looking and prices will therefore incorporate the historical economic growth. This supports the findings that the relationship between the equity long short index and both the change in interest rate expectations and economic growth is insignificant. . This is also consistent with global studies that show that in the short term, there is no correlation between US GDP and S&P 500[17].

[16] http://www.blackstone.com/news-views/blackstone-blog/blog-details/blackstone-publishes-first-black-paper-on-long-short-equity-hedge-funds

[17] https://www.creditwritedowns.com/2014/12/brave-new-world.html

Due to this strategy having a positive bias to the equity market (as explained by the net exposure), it is expected that an equity bear market, as represented by the first dummy variable in the model, would not be significant in explaining the returns of this strategy. By definition of the strategy, the market exposure is hedged and therefore losses will not be as significant as with direct market exposure in the event of a market drawdown.

The Durbin Watson statistic shows that there is no auto-correlation in the residuals.

Robustness check: Results under OLS estimation for Equity Long Short

For comparison, the results of the OLS estimation procedure are reported in Table 2 below. The data uses White's method to cater for the effects of heteroskedasticity. As with the GMM procedure, results are based on t-testing at a 90% confidence level.

Table 2: OLS Estimation Results for Equity Long Short

	Coefficient	Standard Error	t-Statistic	Significance
(constant)	0.007	0.002	3.577	0.006
ALSI	0.245	0.027	9.028	0.000
FRA Curve Shape	0.297	0.412	0.720	0.474
Manufacturing Prod	0.023	0.035	0.645	0.521
ALSI Dummy Var	-0.003	0.002	-1.192	0.239
Rates Expectation Dummy	0.000	0.002	-0.036	0.971

R-squared	0.580
Adjusted r-squared	0.553
Durbin Watson Stat	1.958

The results are consistent with those reported using the GMM estimation procedure in that a dependency exists between the JSE All Share Index (ALSI) and the equity long short strategy index but not with the other factors.

Under the OLS estimation, the contribution of the independent variables to the equity long short strategy index can therefore be described by:

$$R_{\text{Equity Long Short}} = 0.007 + 0.25X_1 + u$$

The variance in returns of the independent variables accounts for 58% of the variability in the returns of the equity long short strategy index over the period Jan 2008 to Dec 2013. The p-values indicate that the JSE All Share Index (ALSI) was the only independent variable that was significant in explaining returns on the equity long short strategy index at the 90% confidence level. The coefficient of 0.25 on the ALSI indicates that when the returns of the ALSI increase by 1%, returns on the Equity Long Short strategy index tend to increase by 0.25% (assuming all other explanatory variables are held constant).

ii. Equity Market Neutral and Quantitative Strategies

Table 3 below shows the results of the GMM estimation procedure between the equity market neutral and quantitative strategies index for the specified market conditions.

Table 3: Estimation output for Equity Market Neutral and Quantitative Strategies

	Coefficient	Standard Error	t-Statistic	Significance
(constant)	0.006	0.001	5.659	0.000
ALSI	0.015	0.017	0.902	0.370
FRA Curve Shape	0.627	0.369	1.701	0.093
Manufacturing Prod	0.065	0.047	1.382	0.171
ALSI Dummy Var	0.003	0.001	3.112	0.003
Rates Expectation Dummy	-0.001	0.001	-0.676	0.501

R-squared	-0.005
Adjusted r-squared	-0.069
Durbin Watson Stat	2.268

The variation in returns of the independent variables tend to have little explanatory power on the variability in the returns of the equity market neutral and quantitative index over the period Jan 2008 to Dec 2013. At a 90% confidence level, the p-values indicate that the shape of the FRA curve and the dummy variable associated with an equity bear market were both significant in explaining returns on the equity market

neutral and quantitative index. At a 90% confidence level, the contribution of independent variables to the equity market neutral and quantitative strategy index can be shown by:

$$R_{\text{Equity Market Neutral and Quants}} = 0.006 + 0.627X_3 + 0.003X_4 + u$$

The coefficient of 0.627 on the shape of the FRA curve indicates that for a 1% change in interest rates expectation, returns on the equity market neutral and Quantitative strategy index tends to increase by 0.627% at a 90% confidence. Similarly, the beta associated with the equity bear market dummy indicates that in a bear market the returns on this strategy index tend to increase by 0.003%.

Contrary to the results shown for the equity long short index, the ALSI is not significant in explaining the returns produced by the equity market neutral strategy index. Market neutral funds tend to exhibit low betas to ensure that the market neutrality targeted is achieved. This is in contrast to the equity long short strategy which targets specific equity risk premia with positive market exposure (Causeway, 2015). It is for this reason that equity market neutral strategies are unlikely to produce returns in excess of the equity risk premium in the long run, but has been shown to offer value in previous bear markets (Vanguard, 2008). Market neutral strategies are therefore considered to offer protection from macro events and are considered to be protection strategies. Macro events that this strategy can potentially protect against include rising real interest rates, and rising inflation.[18] This is

[18] http://www.cogniosfunds.com/announcement.php

consistent with the estimation output above showing the significance of the ALSI bear market and the change in the FRA curve on the strategy returns.

The Durbin Watson statistic shows that there is no auto-correlation in the residuals.

A Robustness Check: Results under OLS estimation for Equity Market Neutral and Quantitative Strategies

The results of the OLS estimation procedure are reported in Table 4 below. The data uses White's method to cater for the effects of heteroskedasticity. As with the GMM procedure, results are based on t-testing at a 90% confidence level.

Table 4: OLS Estimation Results for Equity Market Neutral and Quantitative Strategies

	Coefficient	Standard Error	t-Statistic	Significance
(constant)	0.007	0.001	7.361	0.000
ALSI	0.025	0.009	2.892	0.005
FRA Curve Shape	0.203	0.110	1.851	0.068
Manufacturing Production	0.008	0.128	0.614	0.541
ALSI Dummy Var	0.003	0.001	2.824	0.006
Rates Expectation Dummy	-0.001	0.001	-1.541	0.128

The output of the OLS estimation procedure is consistent with that of the GMM estimation procedure in that both the FRA curve shape and the ALSI bear market

dummy are significant for the equity market neutral and quantitative strategies index at the 90% confidence level. However, the OLS estimation method also finds the ALSI significant for this strategy. This difference is likely due to endogeniety in the model. The estimation equation is defined as:

$$R_{\text{Equity Market Neutral and Quants}} = 0.007 + 0.025X_1 + 0.203X_3 + 0.003X_4 + u$$

iii. Multi-strategy

Table 5 shows the results of the GMM estimation procedure between the multi-strategy style index for the specified market conditions. In this case, a dependency exists between the ALSI and the multi-strategy style index.

Table 5: Estimation output for the Multi-Strategy style index

	Coefficient	Standard Error	t-Statistic	Significance
(constant)	0.006	0.002	3.271	0.002
ALSI	0.111	0.017	6.322	0.000
FRA Curve Shape	0.282	0.662	0.426	0.671
Manufacturing Prod	0.043	0.087	0.492	0.624
ALSI Dummy Var	-0.002	0.002	-1.271	0.208
Rates Expectation Dummy	0.001	0.002	0.472	0.638

R-squared	0.345
Adjusted r-squared	0.306

Durbin Watson Stat	1.703

The contribution of the independent variables to the multi-strategy index can be shown by:

$$R_{Multi\text{-}strategy} = 0.006 + 0.111X_1 + u$$

The variance in returns of the independent variables tends to account for 34.5% of the variability in the returns of the multi-strategy index over the period Jan 2008 to Dec 2013. The p-values indicate that the JSE All Share Index (ALSI) was the only independent variable that was significant in explaining returns on the equity long short strategy index at the 90% confidence level. South African multi-strategy funds have exhibited an average net exposure to equities of between 35% and 50% over the period. (Novare Investments Survey, 2013) As with the equity long short strategy, the tendency of these funds to be long biased (i.e. have positive equity market exposure) implies that these funds will participate in the same direction as the ALSI, and with a magnitude of between 35% and 50% of the moves experienced by the ALSI. This explains why the ALSI is significant in explaining returns of the strategy. The coefficient of 0.11 on the ALSI indicates that when the returns of the ALSI increase by 1%, returns on the Multi Strategy index tend to increase by 0.11% (assuming all other explanatory variables are held constant).

The Durbin Watson statistic shows that there is no auto-correlation in the residuals.

A Robustness Check: Results under OLS estimation for Multi-Strategy

For comparison, the results of the OLS estimation procedure are reported in Table 6 below. The data uses White's method to cater for the effects of heteroskedasticity.

As with the GMM procedure, results are based on t-testing at a 90% confidence level.

Table 6: OLS Estimation Results for Multi-Strategy

	Coefficient	Standard Error	t-Statistic	Significance
(constant)	0.007	0.002	3.437	0.001
ALSI	0.120	0.019	6.488	0.000
FRA Curve Shape	-0.030	0.236	-0.127	0.899
Manufacturing Production	-0.002	0.028	-0.073	0.942
ALSI Dummy Var	-0.002	0.002	-1.217	0.227
Rates Expectation Dummy	0.001	0.002	0.384	0.702

The results are consistent with those reported using the GMM estimation procedure in that a dependency exists between the JSE All Share Index (ALSI) and the multi-strategy index.

Under the OLS estimation, the contribution of the independent variables to the multi-strategy index can therefore be described by:

$$R_{Multi\text{-}strategy} = 0.007 + 0.12X_1 + u$$

iv. Fixed Income Arbitrage

Table 7 below shows the results of the estimation procedure between the fixed income arbitrage style index for the specified market conditions. These results are based on t-testing at a 90% confidence level. In this case, no dependencies exist.

Table 7: Estimation output for Fixed Income Arbitrage index

	Coefficient	Standard Error	t-Statistic	Significance
(constant)	0.005	0.002	1.695	0.094
ALSI	0.027	0.025	1.082	0.283
FRA Curve Shape	-0.233	0.246	-0.948	0.346
Manufacturing Prod	0.029	0.510	0.574	0.568
ALSI Dummy Var	0.002	0.002	1.329	0.188
Rates Expectation Dummy	0.005	0.004	1.360	0.178

R-squared	0.066
Adjusted r-squared	0.006
Durbin Watson Stat	1.356

The contribution of the independent variables to the Fixed income arbitrage strategy index can be shown by:

$$R_{\text{Fixed income arbitrage}} = 0.005 + u$$

The variation in returns of the independent variables tend to account for 6.6% of the variability in the returns of the fixed income strategy index over the period Jan 2008 to Dec 2013.

The p-values indicate that none of the independent or dummy variables tested are significant in explaining returns on the fixed income arbitrage strategy index at the 90% confidence level. Based on these results, we find that the variability in returns of the (independent variables is not significant in explaining) the variability of returns of the HNA fixed income index.

Fixed income arbitrage funds can deploy a range of strategies ranging from yield curve arbitrage, to more complex strategies based on credit risks and macro views on the term structure of interest rates (Chua et al, 2004). Yield curve arbitrage strategies are one the most common strategies deployed by South African fixed income fund managers (Novare Survey, 2013). Abbink (2010) explains that with respect to yield curve arbitrage, trades can take two forms – firstly to trade the level of the yield curve, and thereby trade on whether the level of interest rates implied in the curve is in line with the fund manager's expectation; and secondly to trade around changes in the shape of the curve. This factor considers the daily change in the 12 month segment of the curve to determine if the returns generated by the fixed income arbitrage strategies are affected by the changes in the slope of the curve, but does not take into account a parallel shift in the level of the curve. Due to the nature of the arbitrage strategy, the fund managers may hedge against changes in the level of the yield curve; and may hedge changes in the short dated area of the yield curve with positions in the longer dated instruments on the curve. This hedging behaviour across the term structure is one factor that will explain why no dependency exists between the fixed income strategy and the change in the 12 month term of the yield

curve represented by the FRA curve factor. (Chua et al, 2004. Abbink, 2010. Novare Survey, 2013). Unlike long only bond portfolios, which tend to lose value in a rising rate environment, fixed income arbitrage fund returns are independent of whether interest rate trajectory is one of rising or falling rates. The strategy is more sensitive to the direction of the interest rate spread, and not the level of rates themselves (Tran, 2006). Aurora investment management explains that due to interest rates rising in a non-linear manner, a hedge fund manager is able to employ dynamic trading strategies to capitalise on changes in rates expectations. Global fixed income hedge fund portfolios exhibit a lower sensitivity to changes in interest rates than traditional fixed income investments. 85% of traditional fixed income returns can be attributed to changes in interest rates, whilst only 1% of hedge fund returns can be attributed to changes in interest rates. (Anderson and Cristallo, 2013) This explains why the expectation of rising interest rates as measured by the dummy variable in the model is not significant for the fixed income strategy.

A Robustness Check: Results under OLS estimation for fixed income arbitrage

For comparison, the results of the OLS estimation procedure are reported in Table 8 below. The data uses White's method to cater for the effects of heteroskedasticity. As with the GMM procedure, results are based on t-testing at a 90% confidence level.

Table 8: OLS Estimation Results for Fixed Income Arbitrage

	Coefficient	Standard Error	t-Statistic	Significance

(constant)	0.008	0.002	5.301	0.000
ALSI	0.030	0.021	1.412	0.162
FRA Curve Shape	0.048	0.269	0.180	0.858
Manufacturing Prod	0.017	0.017	1.005	0.318
ALSI Dummy Var	0.001	0.001	0.405	0.687
Rates Expectation Dummy	0.001	0.002	0.549	0.585

The results are consistent with those reported using the GMM estimation procedure in that a dependency exists between the JSE All Share Index (ALSI) and the multi-strategy index.

Under the OLS estimation, the contribution of the independent variables to the multi-strategy index can therefore be shown by:

$$R_{\text{fixed income}} = 0.008 + u$$

Summary of findings

The analysis shows that returns of the hedge fund strategies cannot be easily attributed to the dependent variables specified in the model.

The foregoing results show that the market environment does not have a statistically significant impact on fund performance. The implication is that fund returns are mostly independent of market regimes, and can therefore offer diversification benefit to traditional asset classes. In particular, the fixed income strategy index was not significant for any of the independent variables tested. The implications is that in a

market environment of rising interest rates, which is one that is traditionally negative for long only fixed income portfolios (Anderson and Christallo, 2013), an investor can reallocate a portion of this exposure to a fixed income hedge fund strategy whereby the return profile is agnostic to the direction of interest rates as shown by the rising rates expectation dummy variable.

The equity market neutral and quantitative strategies index was significant for the bear market dummy variable and the change in FRA curve variables. In an environment where the fund of fund investor is expecting an increase in volatility or believes there to be a strong possibility of a bear market, an equity market neutral strategy has shown to be statistically significant.

The equity long short and multi-strategy indices were significant in periods of rising equity markets, and provide an alternative equity exposure to investors who expect equity markets to rise but have a preference for hedged exposure.

These outcomes were based on the analysis conducted on a strategy level. However, there exists a wide dispersion in returns and methods to implement each strategy. The expectation is therefore that the analysis will yield a wider range of sensitivities if conducted at an individual fund level.

The model specification may in some cases be too restrictive as it may not capture all the diverse strategies that hedge fund managers typically deploy. A potential shortcoming of the methodology employed is that the analysis is done at an index level, and therefore may not accurately account for the different methods of implementing each of these strategies by the fund managers.

Part 2 – Developing a portfolio construction framework for the fund of hedge fund industry in South Africa

A fund of hedge fund is often selected as the vehicle to access hedge funds as it provides calculated diversification and outsources the responsibility of analysing and monitoring individual hedge funds. The selection of hedge funds to be included in a fund of funds is therefore crucial. Traditional fund selection involves in-depth qualitative analysis with the fund of fund portfolio manager scrutinising the hedge fund manager's underlying process and philosophy. This is irreplaceable; however, the qualitative appraisal can be enriched through a quantitative process to screen for attractive funds that exhibit statistically significant alpha with limited exposures to traditional risk factors.

The current problem with traditional risk-adjusted measures such as the Sharpe ratio and the Calmar ratio is that these provide no insight into the type of risks employed to generate the realised returns; and does not give one a sense of the stability or predictability of the risk return profile over time.

A more robust framework would decompose the funds return into that portion derived from market betas and exposure to traditional risk factors such as equity and bond market betas, and that component that can be defined as "pure alpha". Pure alpha can be defined as that component which is a result of active bets taken by the fund manager such as security selection, active trading or macro-thematic trading (Shores and Kahn, 2014).

The first part of this portfolio construction framework can use the risk-factor based model as defined by model A on page 37. While this has been analysed for each hedge fund strategy in Part1, it can be extended and applied at individual fund level.

This will allow the investor to identify those funds that are able to generate alpha under different market environments. The fund of fund investor is typically seeking hedge funds that have limited exposure to the defined risk factors that drive volatility and dominate returns in most traditional multi-asset portfolios. The return generated in excess of the betas associated with these traditional asset classes is pure alpha.

While the foregoing results at a strategy level show that the market environment does not have a statistically significant impact on the strategy index performance, an analysis at an individual fund level can yield two possible outcomes. Firstly, the fund level analysis may conform to the strategy level results showing that the market environment similarly has little statistical significance at a fund level. In this case, the fund of fund investor can identify those funds that produce a high alpha over the period under consideration. These high alpha funds will be included in the portfolio regardless of market environment. Alternatively, if the analysis at the individual fund level finds that certain funds are more exposed to specific market environments, the fund of fund investor is then able to opportunistically invest in the appropriate fund dependent on the expected market environment.

Pederson (2014) suggests that the latter scenario is the more likely with the analysis at an individual fund level identifying funds that are more suited to specific market environments. In this case, once the fund of fund investor has filtered the universe to include those funds that are most suited to the anticipated macro environment, the next step is to determine the persistence of the alpha generated by these and its suitability for the fund of fund objective. This can be done by estimating an alpha for each fund and determining the t-statistic for the estimated alpha (Pederson, 2014). To calculate the estimated alpha, the fund of fund investor must first identify a period in history that is qualitatively similar to the market environment that is expected. The

estimated alpha can be derived from the average historical alpha over these similar periods. For example, in a time where the investor believes that the macroeconomic news is signalling an environment of increased volatility, the investor will use an estimated alpha similar to that achieved in similar periods of heightened volatility for each fund.

After obtaining the estimated alpha, the fund of fund investor must determine the stability of this alpha. The t-statistic provides a method to measure whether the value is statistically different from zero. The t-statistic of the estimated alpha is defined as:

$$T_{(alpha)} = \frac{\dot{\alpha}}{\sigma\ (\dot{\alpha})}$$

where: ȧ is the estimated alpha for each fund;

σ(ȧ) is the standard deviation of the estimated alpha

A t-statistic larger than 1.645 signifies that the hedge fund has exhibited persistent alpha over time at a 5% significance level. A negative t-statistic implies that the fund has failed to generate the positive, uncorrelated returns that are expected to improve the investor's risk and return profile. In these instances, the investor may find that they are able to obtain similar exposures to the market betas at a lower cost. The exception to this is for those fund managers generating alpha through their ability to efficiently and actively trade across asset classes and securities. In this case, a low alpha component may be acceptable for a given time period provided that the beta component of the return is significant and consistent (Pederson, 2014).

As part of the portfolio construction framework, an aggregate ranking can be constructed from the T(alpha) and the estimated alpha (ȧ) to produce a composite

measure on which to screen funds that can be used in the construction of fund of fund portfolios that exhibit consistent return profiles in all market environments (Pederson, 2014).

This framework relies on the fundamental assumption that the estimated measures of alpha have significant predictive power of the relative performance of funds into the future.

Optimal number of funds in a portfolio

At this point, the portfolio construction framework has identified those strategies and funds that are positively exposed to a specific market environment. In optimising a portfolio, it is not just the selection of funds, but the number of funds that are integral to the portfolio construction.

A fund of hedge fund provides the investor with calculated diversification and outsources the responsibility of analysing and monitoring individual funds. A critical concern is therefore whether the fund of hedge fund is investing in an optimal number of funds so that the performance and risk characteristics of the pooled portfolio are not compromised. To better understand this issue, this study examines the diversification benefit achieved through incrementally adding funds to a fund of fund portfolio through the simulation methodology detailed on page 44. Through the simulations, a series of equally-weighted fund of hedge fund portfolios of increasing size (N = 5, 6… 40 funds) is created. For each N, an infinite number of portfolio combinations are possible. Funds included in each portfolio simulation were selected randomly to create a definitive representation of this infinite set. For each portfolio, a time series of returns was constructed and used to generate various portfolio risk and return statistics. For each value of N, 100 such random portfolios were

constructed to create a distribution for a portfolio of size N (ie the portfolio return data of these 100 portfolios is used to construct a distribution of returns that is representative of the infinite set of possibilities. These distributions are similarly constructed for volatility, skewness and excess kurtosis.)

The figures that follow show the risk and return behaviour at various portfolios along the distribution for increasing values of N for the Jan 2007 – Dec 2013 period under consideration. The "lower 5%" represents the value above which 95% of the portfolios of funds for each value of N can be found. The "top 5%" point represents the impact on the top 5% of the distribution, and implies that only 5% of the portfolios will produce a result equivalent or better than these observations, and these portfolios are possible through superior fund selection or perfect foresight – factors that are arguably not repeatable in all market environments, or not possible. Portfolios representing the 25%, 50% and 75% points on the distribution have also been included to provide a holistic view of the behaviour of the distribution.

Figure 4 below shows the impact on the fund of hedge fund annualised return of incrementally changing the number of underlying hedge funds in the portfolio. The annualised return is calculated as:

$$Annualised\ return = \left(\prod_{i=1}^{n} (1 + r_i) \right)^{12/n}$$

Where r_i= the monthly return for month i for the fund under consideration

n is the number of months included in the sample

From the figure below, it appears that increasing the number of underlying funds in the portfolio yields a marginally better return profile for all portfolios of funds

represented with the exception of the top 5%. In this case, the return profile deteriorates with the inclusion of each additional fund. This area of the distribution can be seen as exceptionally well selected portfolios. The lower 5%, 25%, 50% and 75% portfolios therefore represent a wider range of the distribution and are more representative of a varied portfolio construction capability. From Figure 4, it appears that the marginal utility on the fund-of-funds return profile for the inclusion of each additional fund peaks at 15 – 17 funds for up to 50% of the portfolios constructed.

Figure 4: Annualised return as a function of size

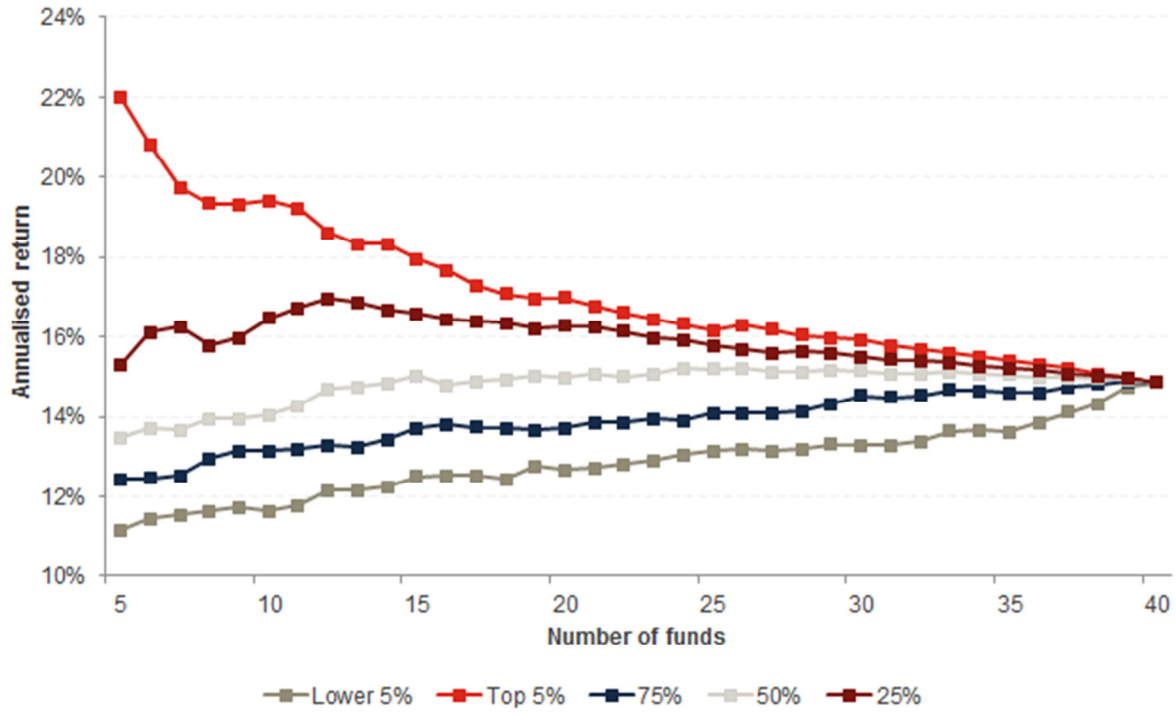


Figure 5 shows the impact on the fund of hedge fund volatility of incrementally increasing the number of underlying hedge funds in the portfolio. The annualised volatility for each fund is calculated as:

$$Annualised\ volatility = \sqrt{\frac{\sum_{i=1}^{n}(R_i - R_{avg})^2}{n-1}} * \sqrt{12}$$

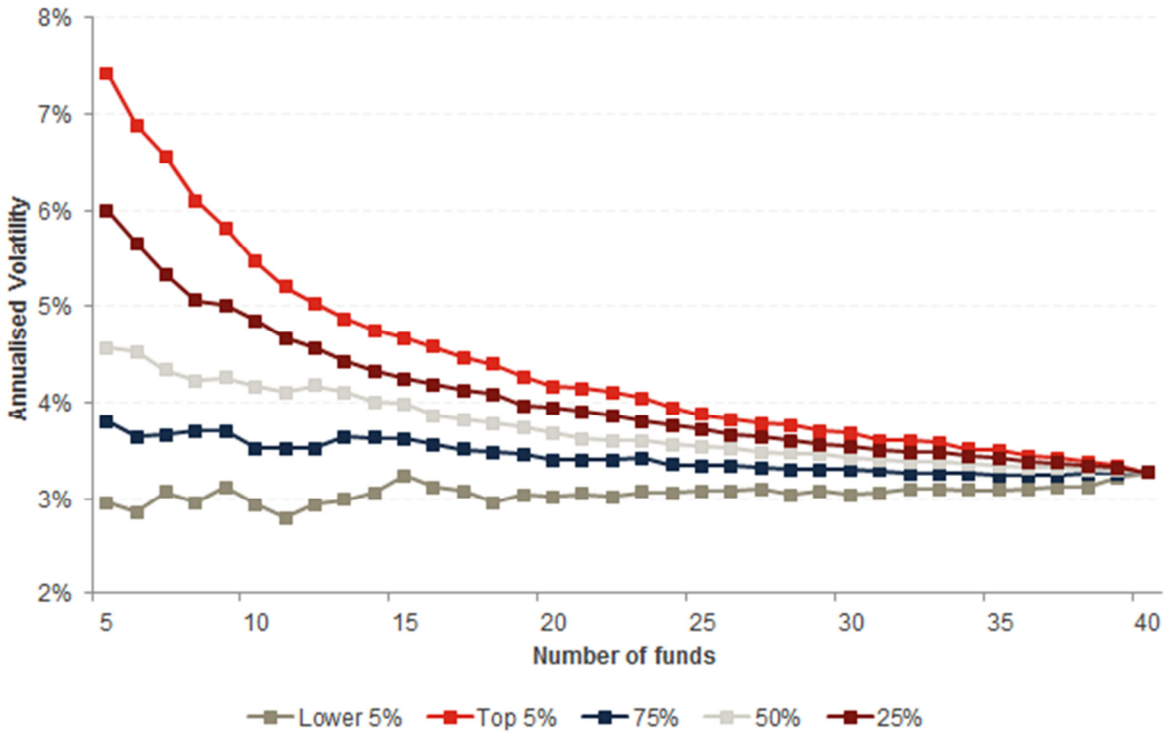
Where R_i is the return for the fund in month *i*

R_{avg} is the average monthly return for the fund over the period

n is the number of months in the sample

From the figure below, it appears that increasing the number of underlying funds sees deterioration in the volatility profile for portfolios representative of the top 5%, 25%, 50% and 75% of the distribution, while there is little impact on the volatility profile of the fund of fund for the lower 5% portfolios. The deterioration in the volatility profile for the bulk of portfolios constructed can be attributed to the effect of diversification as more funds are included in the portfolio. The results show that there is little difference to the volatility of the lower 5% of the portfolios constructed with the increase in the number of funds. The marginal utility of the inclusion of each additional fund to the volatility of the fund of fund portfolio diminishes once the number of funds exceeds 20 for the bulk of distribution as illustrated by the benefit to all portfolios for the top 75% of portfolios constructed.

Figure 5: Annualised volatility as a function of size



A portfolio that is normally distributed is one where the mean return is the same as the average return, and the standard deviation of returns conforms to the normal distribution curve. The standard deviation represents the amount by which the returns deviate from the mean. Both the skewness and excess kurtosis of a normal distribution are zero implying that the distribution is symmetric around the mean with the probability of extreme outcomes unlikely. A return series that follows a normal distribution enables risk to be represented within a clearly defined range. Doane and Seward (2011) argue that desirable utility functions should exhibit decreasing absolute risk aversion, implying that investors should have preference for positively skewed asset returns.

Figure 6 below shows the impact on the fund of hedge fund portfolio skewness as the number of underlying hedge fund managers in the portfolio is incrementally

increased. Skewness is a measure of asymmetry of a distribution, and can be calculated as follows:

$$Skewness = \frac{n}{(n-1)(n-2)} \sum \left(\frac{r_i - r_{avg}}{s}\right)^3$$

Where r_i is the return for the fund in month *i*

r_{avg} is the average monthly return for the fund over the period

n is the number of months in the sample

s is the standard deviation of the sample

A portfolio that exhibits a skewness of zero will tend to follow a normal distribution and is said to be symmetrical about the mean, which means the occurrence in both the left hand and right hand tails of the distribution are roughly equal. For a value greater than zero, the distribution is positively skewed. Positive skewness indicates that the right hand side tail of the distribution is longer than the left hand tail which is typical of frequent small losses and a few large gains. Similarly, for a value less than zero, the distribution exhibits negative skewness. Negative skewness indicates that the left hand tail of the distribution is longer than the right hand tail which is typical of frequent small gains and a few large losses.

From Figure 6, it can be seen that for the lower 5% of fund of fund portfolios the inclusion of each additional fund for the first 20 funds appear to meaningfully reduce the negative skewness of the portfolio. Each additional fund thereafter has a marginal impact on the portfolio skewness. This implies that the inclusion of more than 20 funds will have little benefit on the overall portfolio skewness. For the upper 5% of the portfolio of funds, the positive skew of the distribution is compromised

once the number of funds in the portfolio exceeds 12. As explained, this can be seen as that portion of the distribution where the portfolios of funds can be seen as exceptionally well selected and not necessarily representative of the bulk of the distribution.

Similarly, the lower 5% of portfolios represents little fund selection skill when constructing these portfolios. It is expected that a large number of funds in the sample exhibit a negative skew, and therefore a large number of portfolios of funds tend to exhibit a negative skew. This is supported by the fact that the top 5% of the portfolios of funds constructed is the only portion of the distribution that is exhibiting positive skew. However, the inclusion of each additional fund to the portfolio does have the effect of reducing the negative skewness of the portfolios representing the remainder of the distribution.

The incorporation of skewness in the optimisation process results in the optimal portfolio being pushed further up the efficient frontier. This implies that an investor is able to achieve a higher return for an equivalent level of risk once skewness is included in the decision process (Doane and Seward (2011)).

Figure 6: Skewness as a function of size

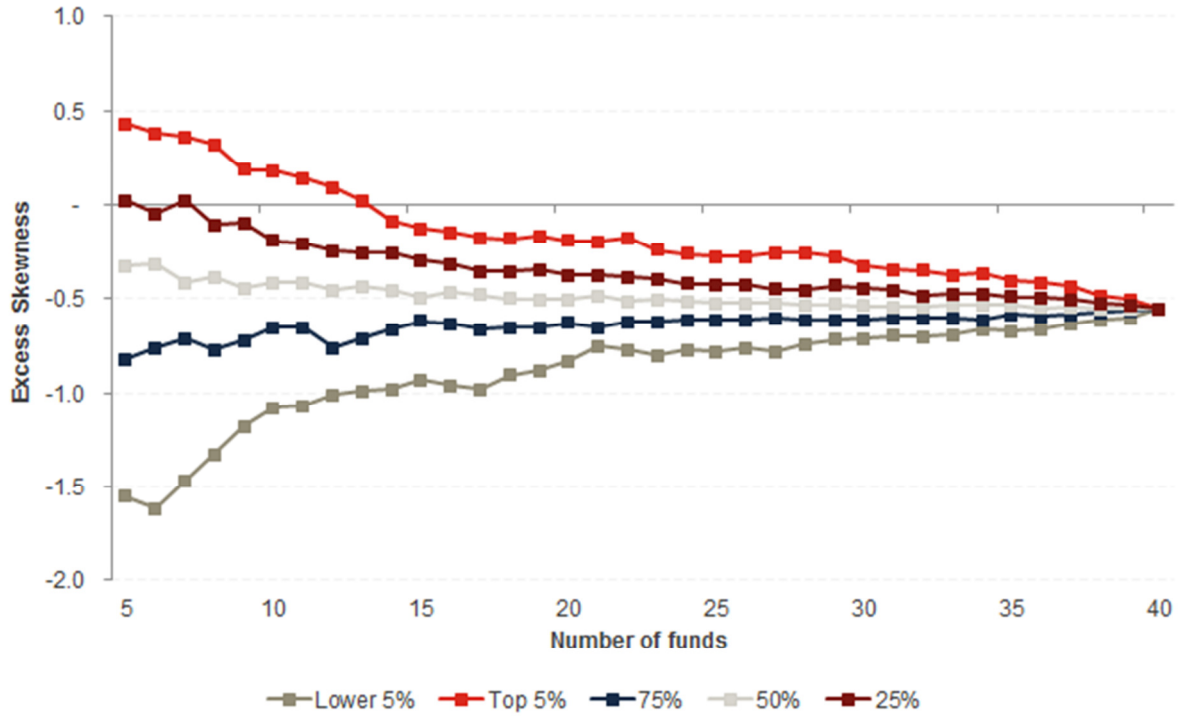


Figure 7 below shows the impact on the fund of hedge fund portfolio kurtosis as the number of underlying hedge funds in the portfolio is incrementally increased. Kurtosis is the fourth moment of a distribution which measures whether the distribution is peaked or flat relative to a normal distribution. Kurtosis is calculated by:

$$Kurtosis = \left[\frac{n(n+1)}{(n-1)(n-2)(n-3)}\sum\left(\frac{r_i - r_{avg}}{s}\right)^4\right] - \frac{3(n-1)^2}{(n-2)(n-3)}$$

Where r_i is the return for the fund in month *i*

r_{avg} is the average monthly return for the fund over the period

n is the number of months in the sample

s is the standard deviation of the sample

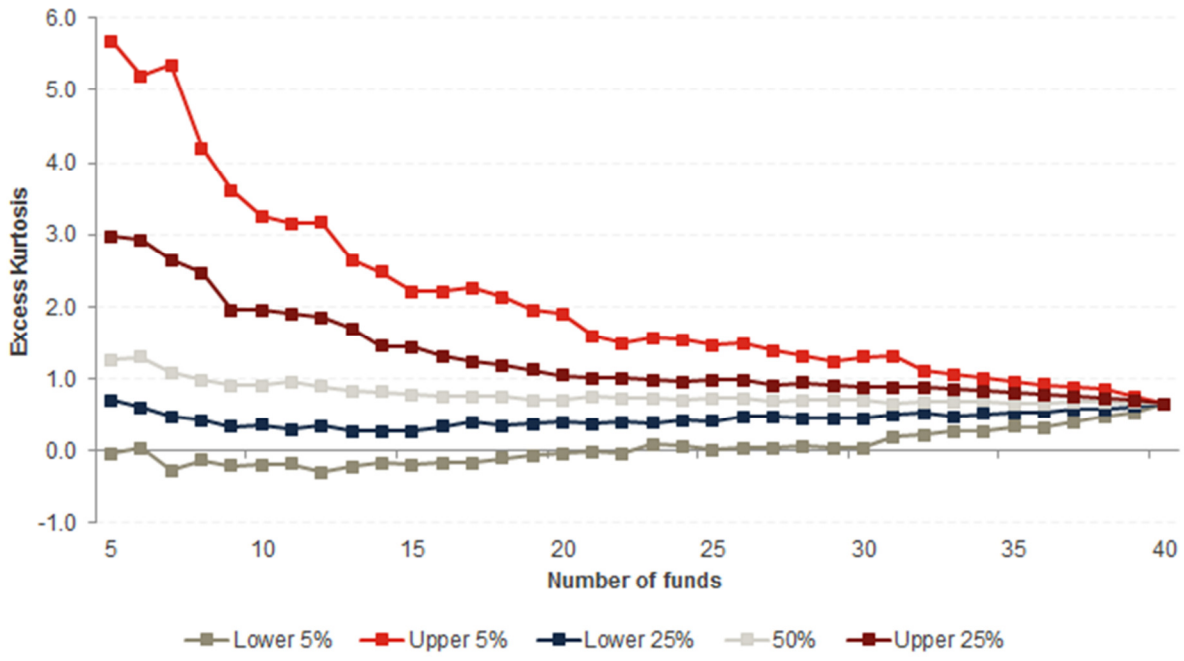
A high excess kurtosis is indicative of a peaked distribution with fat tails (i.e., a large number of outcomes occurring around the mean of the distribution, with fat tails which means there exists a high probability for extreme values). This is known as a leptokurtic distribution. A platykurtic distribution is characterised by a low excess kurtosis value. This is a flatter distribution with the values spread wider around the mean, and the probability of extreme values is lower.

From the figure below, it can be seen that the lower 5% of fund of fund portfolios exhibited a distribution that is approximately mesokurtic. A mesokurtic distribution is one that is similar to the kurtosis of a normally distributed data set. The inclusion of each additional fund for the first 20 funds does not appear to have any significant impact on the excess kurtosis of the portfolio. Each additional fund thereafter increased the portfolio kurtosis, resulting in an increasing leptokurtic distribution (i.e., the excess kurtosis value increases). This is not desirable, as this will by definition result in heavier tails in the distribution implying a higher probability of extreme outcomes. For the top 5% and 25% portfolios of funds, the distribution becomes less leptokurtic with each additional fund included in the portfolio.

The inclusion of funds that are not similarly positioned will create a diversification benefit, and reduce the tails of the distribution. Lhabitant and Learned (2004) find that changes in kurtosis are unpredictable over time and across styles. Furthermore, funds may capture the same systematic risks through the underlying positioning. For example, if the randomly selected funds were from the same strategy, the underlying positioning could be similar, and therefore the inclusion of these similar funds will not

yield any significant diversification benefit and the tails of the distribution will remain fat.

Figure 7: Kurtosis as a function of size



Summary of findings

Figure 8 below depicts a risk adjusted return measure for each of the percentile points discussed through the document. This is calculated simplistically as:

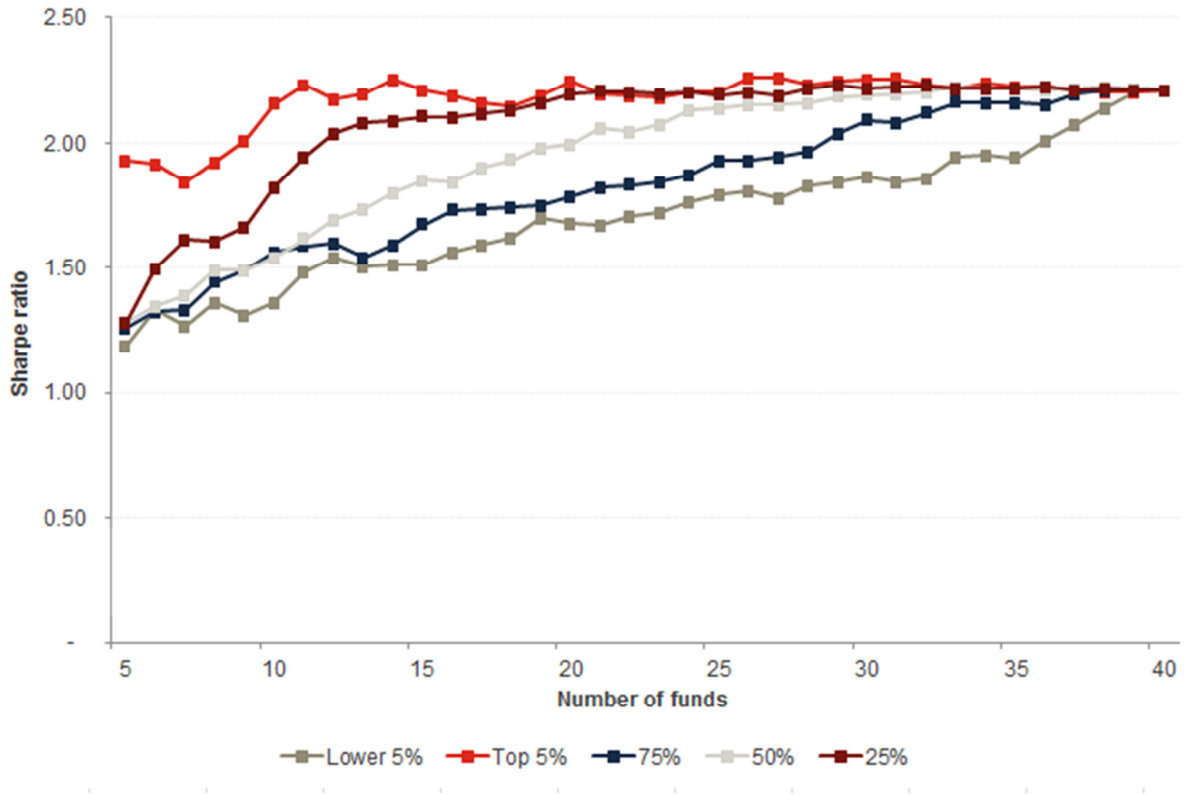
$$Risk\ adjusted\ return = \frac{Annualised\ Return - Risk\ Free\ Rate}{Annualised\ Volatility}$$

where the Risk Free Rate used is the STeFI cash rate.

The Sharpe ratio calculates the average return earned over a risk free rate per unit of risk assumed. The ratio enables investors to compare funds on a risk adjusted basis to determine if one is being adequately compensated for the risk being assumed. A higher Sharpe ratio implies that a fund has produced a higher return relative to the risk taken (Doane and Seward (2011)).

For each of the points of the distribution being represented, the curve appears to flatten between 20 and 25 funds implying that the risk-return benefit of including funds starts to dissipate beyond 20 funds, with the exception for the top 5% of the distribution where the curve flattens at 15 funds.

Figure 8: Sharpe ratio as a function of size



A more detailed summary is provided in the table below for the top 5% and lower 5% of the portfolios of funds that were constructed. The top 5% represents those portfolios that are constructed with superior fund selection ability, while the lower 5% represents those portfolios with limited fund selection ability and above which 95% of the distribution lies. (The remaining portfolios lie between these two points and similar explanations can be extrapolated from these extreme points.)

Table 9: Summary of results of increasing funds on the 5th and 95th percentiles

	Results of increasing number of funds on	
	Volatility and Return	**Higher Moments**
Top 5% portfolios	The return and volatility profiles of the portfolio of funds decline as the number of funds included in the portfolio increases. The top 5% of the portfolios is likely to incorporate those funds that tend to exhibit a high return with the commensurate volatility. As a result by introducing more funds into the portfolio, the volatility of the portfolio is reduced through diversification across a larger number of funds. This diversification benefit comes at a cost on the return. Looking at the risk-return measure used in Figure 8, it can be inferred that for the top 5% of the distribution, the risk return	The excess kurtosis declines as the number of funds increases, indicating that as the number of funds increases the likelihood of extreme outcomes (both positive and negative) declines. This is congruous with the findings on volatility, which showed that the volatility of the portfolio also declines. Simultaneously, the skewness of the portfolio becomes less positive with the inclusion of more funds. As the number of funds increases the large extreme outcomes become less likely due to the diversification obtained by including more funds in the portfolio.

	benefit starts to decline once the number of funds exceeds 15.	
Lower 5% portfolios	The sharpe ratio is the lowest for these portfolios. This implies that the investor is earning a relatively low return for the risk assumed. Looking specifically at the return profile, returns improve as the number of funds included increases suggesting that as the number of funds increases, so does the possibility of achieving a higher return. However, it is important to note that the absolute level of return is the lowest for this point of the distribution. The marginal benefit on the return profile peters out once the number of funds exceeds 20.	The inclusion of funds into the lower 5% of portfolios results in a reduction in negative skewness on the portfolios. This is supportive of the results of the return and volatility of the portfolios, as the increase in skewness is indicative a more favourable distribution.

For the fund of fund investor to effectively determine the optimal number of funds to be included in the portfolio, both the fund of hedge fund objective and the investor's fund selection capability must be taken into consideration. An investor with superior

fund selection capability will consider the profile representing the top 5% of portfolios of funds of size N, while an investor with little fund selection skill might consider the lower 5%. The investor is then able to determine the optimal number of funds based on the fund of hedge fund objective. For example, for an investor with little fund selection expertise a fund of hedge fund targeting an annualised absolute return of 12-14%, with a targeted volatility of 3-4% will have 20 funds included in the portfolio of funds based on the analysis above for the lower 5% portfolios. For an investor with a greater degree of confidence in their ability to achieve a portfolio that will perform closer to the portfolio of funds representing the midpoint on the distribution, the number of funds is then closer to 15 to achieve the desired return outcome at the targeted volatility. This conclusion is reached by determining the of number of funds that have produced the targeted return from Figure 4, and similarly finding the number of funds that have produced the expected volatility from Figure 5 for the desired confidence level.

One shortcoming of this methodology is that only funds that have a return history over the full period have been included in the analysis. Consequently, any funds that have entered the universe after the starting period of the analysis that may significantly affect the risk and return profiles of a fund of fund has been excluded from the analysis.

Chapter 5: Conclusion

Extensive research has been conducted to examine the performance of global hedge fund strategies under different market environments, specifically under bull and bear market conditions, but with no similar studies directed at the South African hedge fund landscape. This paper developed a portfolio construction framework for a fund of hedge fund in the South African context. Classical mean variance optimisation is often used for the portfolio construction of fund of hedge funds, but this tends to underrepresent the risk due to the non-normal characteristics of hedge funds. The inclusion of the higher moments in the analysis, as well as the analysis of the performance in different market environments takes into account this non-normal nature of the distributions.

The framework is predicated on the assumption that the fund of fund portfolio manager has a view on the impending macro-environment. The first step analysed the performance of the major South African hedge fund indices under different market conditions to determine how the various strategies performed in different environments. The factors considered in the model were the JSE All Share Index, the expectation of rising or falling rates as measured by the yield curve, the local manufacturing production as a proxy for South African economic growth, a dummy variable to assess the performance of these strategies in a bear market, and a second dummy to analyse the strategies in an environment where there is an expectation of rising interest rates.

The GMM estimation procedure was used for the analysis, and the results of a standard OLS estimation were also included as a robustness check for the analysis. The GMM estimations found that the equity long short and multi strategy indices

were statistically significant in a period of rising equities. The equity market neutral and quantitative strategies index was significant in regimes where there was a change in interest rate expectations as represented by the shape of the FRA curve, as well as being significant in bear markets. The fixed income arbitrage index was not statistically significant for any of the specified variables. The OLS estimations confirmed all the results produced by the GMM estimation with the only exception being that the OLS estimation found that in addition to the shape of the FRA curve and the ALSI bear market, the performance of the ALSI was also significant for the equity market neutral and quantitative strategies index. This discrepancy can be explained by the endogeniety present in the model.

The outcome from this analysis was used as the foundation to constructing a portfolio construction framework. The analysis shows that returns of the hedge fund strategies cannot be easily attributed to the dependent variables specified in the model. However, this in itself has implications for the role of the hedge fund strategies in traditional portfolios.

For the fixed income hedge fund strategy index, the results of the analysis show that the strategy returns are agnostic to the expectation of rising rates. In a market environment of rising interest rates, which is one that traditionally negative for long only fixed income portfolios, an investor can reallocate a portion of this exposure to a fixed income hedge fund strategy to protect capital and earn a diversified return stream.

The equity market neutral index showed a positive dependence when the market was in a bear market phase. Therefore, in an environment where the fund of fund investor is expecting an increase in volatility or believes there to be a strong

possibility of a bear market, an allocation to an equity market neutral strategy can be deemed appropriate.

The equity long short and multi-strategy indices were significant in periods of rising equity markets, and provide an alternative equity exposure to investors who expect equity markets to rise but have a preference for hedged exposure.

The small r-squared values produced by the estimation procedures substantiate that the strategies employed by fund managers to generate returns extend beyond playing with the specified risk factors in a static fashion. There exists a wide dispersion in returns and methods to implement each strategy. The model specification may in some cases be too restrictive as it may not capture all the diverse strategies that hedge fund managers typically deploy. A potential shortcoming of the methodology employed is that the analysis is done at an index level, and therefore may mask the implementation nuances that these fund managers exploit in execution of the strategy.

This study proposes that the analysis discussed to ascertain the performance of the strategies in different market regimes is extended to an individual fund manager level. This will enable the investor to identify those funds that are particularly suited to different market environments. The next step in the framework is to determine the persistence of the alpha generated by the each of the funds identified as positively exposed to the expected environment and to determine the persistence of the alpha generated and its suitability to the fund of fund objective. This is done by estimating an alpha for each manager and determining the t-statistic for the estimated alpha. The estimated alpha is derived from the average historical alpha over a period where the market environment is qualitatively similar to the environment expected, while the

t-statistic is used to determine the stability of the alpha produced. An aggregate ranking can be constructed from the t-statistic alpha and the estimated alpha to produce a composite measure to screen funds that produce a stable alpha in similar environments to the environment that is anticipated. The result of this screening process is a list of funds with a stable and significant alpha for the environment that the fund of hedge fund portfolio manager believes likely. The alphas were not computed as part of the analysis as the framework is predicated on a forward-looking macroeconomic analysis, such that the fund of fund investor will be required to identify a similar environment in history to the one anticipated.

Once the funds have been filtered to include only those with a stable and significant alpha, the question becomes one of how many funds should be included in the portfolio. This was analysed by graphically considering the marginal utility for each additional fund to a portfolio of funds. The study takes into account the impact on the return profile, volatility profile, skewness and kurtosis of the simulated portfolios. The inclusion of the higher moments in the analysis is to incorporate the non-normal nature of the distribution.

The study finds that as the number of funds in the portfolio exceeds twenty the marginal utility of each fund diminishes, for the majority of the distribution under consideration. To more closely approximate the number of funds to be included in a portfolio, both the fund of hedge fund objective and the investor's fund selection capability must be taken under consideration. An investor with superior fund selection capability will consider the representation of the top 5% of the distribution, while an investor with little fund selection skill will consider the lower 5% profile. The investor is then able to determine the optimal number of funds based on the fund of

hedge fund objective from the point on the distribution corresponding to the investors fund selection skill.

Suggestions for further research

The analysis conducted on the performance of hedge fund strategies under the different market environments has been conducted at an index level and therefore does not factor in specific style biases and implementation nuances that the individual fund managers employ. A more granular analysis at either a sub-strategy or individual fund level will yield more comprehensive results.

A further refinement is to expand on the number of macroeconomic variables and consequently a broader spectrum of market environments.

One shortcoming in the analysis of the optimal number of funds is that only funds that have a return history over the full period have been included in the study. Consequently, funds that may have closed or stopped reporting due to poor performance or reaching capacity, and any funds that have entered the universe after the starting period of the study have been excluded. To cater for survivorship bias and for completeness the research can be extended to include these funds.

Due to the South African hedge fund industry still being in its infancy compared to global counterparts, the period under consideration spans the January 2007 to December 2013 period. As the industry continues to grow and more data becomes available, different portfolio construction methodologies can be defined and tested.

Bibliography

1. Abbink, John B. (2010). 'Alternative Assets and Strategic Allocation: Rethinking the Institutional Approach'. New Jersey, John Wiley & Sons Ltd.
2. Agarwal, Vikas. Naik, Narayan Y. (2000). 'Multi-Period Performance Persistence Analysis of Hedge Funds' Working Paper. Available online at: http://papers.ssrn.com/sol3/papers.cfm?abstract_id=190389
3. Agarwal, Vikas. Naik, Narayan Y. (2004) 'Risks and Portfolio Decisions Involving Hedge Funds'. The Review of Financial Studies. pp 63 -98. Available online at: http://www2.gsu.edu/~fncvaa/RiskandPortfolioDecisionsinvolvingHedgeFunds-RFSversion.pdf
4. Amin, Gaurav S. Kat, Harry M. (2002). 'Portfolio of Hedge Funds: What Investors Really Invest In.' Cass Business School Research Paper. Available online at: http://papers.ssrn.com/sol3/papers.cfm?abstract_id=296642Amo, Anne-Valere. Harasty, Helene. Hillion, Pierre. (2007). 'Diversification Benefits of Fund of Hedge Funds: Identifying the Optimal Number of Hedge Funds'. The Journal of Alternative Investments, Fall 2007.
5. Anderson, John. Cristallo, Dennis. (2013). "Hedge Funds: A Potential Tool to Reduce Interest Rate Risk. JP Morgan Chase & Co. Available online at: https://am.jpmorgan.com/gi/getdoc/1383169832327
6. Ang, Andrew. Rhodes-Kropf, Matthew. Zhao, Rui. (2005) 'Do Fund-of-Funds Deserve Their Fees-on-Fees?' National Bureau of Economic Research. Working paper 13944. Available online at: http://www.nber.org/papers/w13944.pdf

7. Baccman, Jean-François. Gawron, Gregor. (2004). 'Fat tail risk in portfolios of hedge funds and traditional investments'.RMF Investment Group. Available online at: http://www.intercontilimited.com/mfutsarchive/ssrn-id492643.pdf
8. Baccman, Jean-François. Scholz, Stefan. (2003). 'Alternative Performance Measures for Hedge Funds.' The AIMA Journal, June 2003.
9. Barabrino, Frank (2007). 'Leverage, Hedge Funds and Risk.' Available online at: http://www.nepc.com/writable/research_articles/file/09_07_nepc_leverage_hf_and_risk.pdf
10. Baum, Christopher F. Schaffer, Mark E. Stillman, Steven. (2003). 'Instrument Variables and GMM: Estimation and Testing'. Stata Journal Volume 3. pp 1 – 31. Available online at: http://www.stata-journal.com/article.html?article=st0030
11. Blanchard, O. (2013). Macroeconomics (6th Edition). New Jersey: Pearson Prentice Hall
12. Brown, Stephen J. Gregoriou, Greg N. Pascalau, Razvan C. (2011) 'Diversification in Fund of Hedge Funds: It is Possible to Overdiversify?' Available online at: http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1436468
13. Bruder, Benjamin. Darolles, Serge. (2010) 'Portfolio Allocation of Hedge Funds'. Lyxor Asset Management. Available online at: http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1804511
14. Canto, Victor. (2006). 'Understanding Asset Allocation: an inituitive approach to maximising your portfolio.' Pearson Education. New Jersey.

15. Capocci, Daniel. Corhay, Albert. Hubner, Georges. (2003) 'Hedge Fund Performance and Persistence in bull and bear markets' Available online at: http://papers.ssrn.com/sol3/papers.cfm?abstract_id=483222
16. Carlson, Mark. Steinman, Jason. (2008) 'Market Conditions and Hedge Fund Survival' Working paper. Finance and Economics Discussion Series. Available online at: http://www.federalreserve.gov/pubs/feds/2008/200828/200828pap.pdf
17. Chua, Choong Tze. Koh, Winston T.H., Ramaswamy, Krishna (2004). 'Profiting from Mean-Reverting Yield Curve Trading Strategies'. Singapore Management University. University of Pennsylvania. Available online at: http://ink.library.smu.edu.sg/cgi/viewcontent.cgi?article=3488&context=lkcsb_research
18. Cazalet, Zelia. Zheng Ban (2014). 'Hedge Funds in Strategic Asset Allocation.' White Paper Issue #11. Lyxor Asset Management. Available online at: http://www.lyxor.com/fileadmin/_fileup/lyxor_wp/document/95/.
19. Darolles, Serge. Vaissié, Mathieu. (2014). 'The Fund of Hedge Fund Selection Puzzle: A Pragmatic Approach to Identify the X-Factor'. Edhec Business School. Available online at: http://www.edhec-risk.com/edhec_publications/all_publications/RISKReview.2014-04-16.2312/attachments/EDHEC_Working_Paper_The_FoHF_Selection_Puzzle_F.pdf
20. Davies, Ryan J. Kat, Harry M. Lu, Sa. (2004) 'Fund of Hedge Funds Portfolio Selection: A Multiple-Objective Approach.' Working Paper. Alternative Investment Research Centre. Available online at: http://www.intelligenthedgefundinvesting.com/pubs/rb-rdhksl.pdf

21. Doane, David P. Seward, Lori E. (2011) ‘Measuring Skewness: A Forgotten Statistic?’ Journal of Statistics Education. Volume 19. Available online at: http://www.amstat.org/publications/jse/v19n2/doane.pdf
22. Edwards, Franklin R. Caglayan, Mutafa Onur. (2000) ‘Hedge Fund and Commodity Fund Investment Styles in Bull and Bear Markets’. City University of New York. Available online at: http://papers.ssrn.com/sol3/papers.cfm?abstract_id=281522
23. Favre, Laurent. Galeano, José-Antonio. (2002) ‘Mean-Modified Value-at-Risk Optimization with Hedge Funds.’ The Journal of Alternative Investments, Fall 2002.
24. Fung, William. Hsieh, David A. Naik, V Narayan Y. Ramadorai, Tarun. (2008) ‘Hedge Funds: Performance, Risk, and Capital Formation’. The Journal of Finance. Available online at: http://intranet.sbs.ox.ac.uk/tarun_ramadorai/TarunPapers/fung_hsieh_naik_ramadorai.pdfGéhin,
25. Walter. Vaissié, Mathieu. (2004). ‘Hedge Fund Indices: Investable, Non-Investable and Strategy Benchmarks’. Edhec Risk and Asset Management Research Centre. Available online at: http://www.edhec-risk.com/edhec_publications/RISKReview109941045609841 8642/attachments/HFIndicesInvestableNonInvestableandStrategyBenchmarks.pdf
26. Giamouridis, Daniel. Vrontos, Ioannis D. (2007) ‘Hedge Fund Portfolio Construction: A Comparison of Static and Dynamic Approaches.’ Journal of Banking Finance, Volume 31, Issue 1. pp 199 – 217.
27. Hart, Ryan. Magnusen, Lara. (2014.) ‘Long Short Equity: Choosing Alpha over Beta’. Altegris Advisors. Available online at:

http://www.altegris.com/~/media/Files/White%20Paper/ACAWPLSEquity2014FINAL1313NLD0929142.pdf

28. Horejs, Mallory. ‘Long short equity handbook’. Morningstar. Available online at: advisor.morningstar.com/uploaded/pdf/Alt_Long-ShortEquity.pdf
29. Heidorn, Thomas. Kaiser, Dieter. Lucke Daniel. (2013) ‘The value add of hedge fund styles in multi-asset portfolios: A new approach based on bull and bear market betas’. Review of Accounting and Finance Vol. 12 No. 1, pp 44 - 59
30. Jagannathan, Ravi. Malakhov, Alexey. Novikov, Dmitry. (2010) ‘Do Hot Hands Exist among Hedge Fund Managers? An Empirical Evaluation’. The Journal of Finance 65 -1, pp 217-255.
31. Jones, Chris. (2007) ‘Hedge fund of funds: A guide for investors’. West Sussex, John Wiley & Sons Ltd.
32. Lamm, R. McFall Jr. (2003) ‘Asymmetric Returns and Optimal Hedge Fund Portfolios.’ The Journal of Alternative Investments, Fall 2003.
33. Leung, Seng Yuen (2006). ‘Yield Curve Analysis and Fixed-income Arbitrage’. Hong Kong University of Science and Technology. Available online at: http://www.math.ust.hk/~malwu/seminar/YCAnalysis.pdf
34. Lhabtiant, Francois-Serge (2002). ‘Hedge Funds: Myths and Limits’. West Sussex, John Wiley & Sons Ltd.
35. Lhabitant, François-Serge. Learned De Piante Vicin, Michelle. (2004) ‘Finding the Sweet Spot of Hedge Fund Diversification’. Edhec Risk and Asset Management Research Centre. Available online at: http://www.edhec-risk.com/events/uploads/HFDay/doc/S1_Finding_the_Sweet_Spot_of_Hedge_Fund_Diversification.pdf

36. Lo, Andrew (2008). 'Hedge Funds: An analytical perspective', New Jersey, Princeton University Press.
37. Patel, Kartik (2007). 'How Many Fund Managers Does a Fund of Funds Need?' Prisma Capital Partners.
38. Pederson, Niels. (2013). 'A Quantitative Framework for Hedge Fund Manager Selection'. PIMCO. Available online at: http://www.pimco.com/en/insights/pages/a-quantitative-framework-for-hedge-fund-manager-selection.aspx
39. Peskin, Michael W. Urias, Michael S. Anjilvel, Satish I. Boudreau, Bryan E. (2000) 'Quantitative Strategies: Why Hedge Funds Make Sense'. Morgan Stanley. Available online at: http://www.morganstanley.com/institutional/qs/pdfs/msdw0011_why_hedge_funds.pdf
40. Phillips, Christopher B. (2006). 'Understanding Alternative Investments: A Primer on Hedge Fund Evaluation.' Vanguard Investment Counselling and Research. Available online at: https://personal.vanguard.com/pdf/s554.pdf
41. Ranaldo, Angelo. Favre, Laurent. (2005). 'Hedge Fund Performance and Higher-Moment Market Models.' The Journal of Alternative Investments, Winter 2005.
42. Sandte, Holge (2012). 'Stock Markets vs GDP Growth: A Complicated Mixture'. WestLB Mellon Asset Management. Available online at: http://us.bnymellonam.com/core/library/documents/knowledge/AlphaTrends/Stock_Markets_vs_GDP.pdf

43. Sandvik, Sjur Hordvik. Frydenberg, Stein. Westgaard, Sjur. Heitmann, Rolv Kristian. (2011) 'Hedge Fund Performance in Bull and Bear Markets. Alpha Creation and Risk Exposure.' Journal of Investing; Spring 2013.
44. Schneeweis, Thomas. Kazemi, Hossein. Szado, Edward. (2012). 'Hedge Fund Return-Based Style Estimation: A Review of Comparison Hedge Fund Indices'. The Journal of Alternative Investments; Fall 2012.
45. Selbovitz, David J. Joffe, Adam B. (2013) 'Managing Downside Risk with Liqud Equity Alternatives'. The Bank of New York Mellon. Available online at: https://www.bnymellon.com/us/en/our-thinking/foresight/managing-downside-risk-with-liquid-equity-alternatives.jsp
46. Shores, Sara. Kahn, Ronald. (2014) 'Getting strategic on beta' Institutional investor. September 2014.
47. Signer, Andreas. Favre, Laurent. (2002) 'The Difficulties of Measuring the Benefits of Hedge Funds' The Journal of Alternative Investments, Summer 2012.
48. Sun, Zheng. Wang, Ashley W. Zheng, Lu. (2014) 'Hedge Fund Performance Persistence over Different Market Conditions: Only Winners in Tough Times Repeat'. Available online at: http://ssrn.com/abstract=2249033
49. Tran, Vinh Q. (2006). 'Evaluating Hedge Fund Performance'. New Jersey, John Wiley & Sons Ltd.
50. Zsohar, Peter. 'Short introduction to the Generalised Method of Moments'. Hungarian Statistical Review, Special number 16. Available online at: http://www.ksh.hu/statszemle_archive/2012/2012_K16/2012_K16_150.pdf