University of Cape Town – Masters in Financial Management

Hedge Fund Factorization and Benchmarking

Understanding hedge fund performance, benchmarking and the reward system for hedge fund managers

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This paper is dedicated to my wife. Without her love, guidance and constant support this paper would never have been completed. Now, as always, I owe everything I have to her.

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Abstract

Hedge funds give portfolio managers access to more tools to aid in better portfolio construction. The introduction of tools such as leveraging and shorting provided managers with the ability to augment exposures to different asset classes. The result is the ability to create portfolios with uncorrelated returns without having to invest in a plethora of asset classes thus providing better risk adjusted returns.

This paper tests whether hedge funds in fact contain less exposure to individual asset classes than their long-only counterparts. In particular, the perception of uncorrelated returns has led to hedge funds being benchmarked against absolute return targets while charging performance fees higher than the typical long-only fund. If hedge fund returns are correlated with those of the asset class in which they invest, the available risk premia available in that asset class may drive returns more than manager skill.

In circumstances where hedge fund returns are in fact correlated with asset class returns, then the benchmarks used to measure hedge fund performance ought to capture the perpetual risk premia of the asset classes for better performance measurement and performance fee rewards.

This dissertation closely follows Hasanhodzic and Lo (2007) who sought to find the quantum of hedge fund returns attributable to asset class returns; that information was then used to create low-cost clones of typical hedge fund strategies. This dissertation also tested the strength of the relationship between hedge fund and asset class returns but used the result to build linear clones for benchmarking rather than as an alternative to hedge funds.

What also distinguishes this dissertation is the jurisdiction: Hasanhodzic and Lo (2007) examined global hedge funds while this dissertation focusses on the South African hedge fund industry. The HedgeNews Africa database is the data source for South African hedge fund returns (from some 412 funds though only 160 of those are currently active). Database returns existed for the period June 1998 to June 2020. The regression assessment conducted regressed the returns of various hedge fund strategies against the returns of the relevant asset classes. The result of the regressions reveals significant coefficients relating to different asset class independent variables. The significant relationships accord with the logical association of certain hedge fund strategies with particular asset classes. For instance, equity long-short funds had a large and significant coefficient relative to

equity market returns. Based on the regressions, clone benchmark portfolios were created which performed similarly to the various strategies in the ex-ante period from January 2019 to 2020. This lends credence to the idea that better benchmarks can be specified for hedge fund managers.

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CHAPTER 1: INTRODUCTION

Understanding the hedge fund investment vehicle starts with the conceptual understanding of mutual funds. In South Africa these are referred to as unit trusts or collective investment schemes. For consistency the term “mutual fund” will be used to denote this collection of vehicles both in South Africa and globally. Mutual funds are investment vehicles which pool investor funds for investment in securities across different asset classes or in a single asset class. The funds were typically professionally managed according to the investment objective and mandate stipulated in the fund particulars (Agarwal & Naik, 2004). For single asset class mutual funds this generally meant that the fund invested in select asset classes ranging in risk from equity to income-based securities. The nature of the investment thus entailed a basket (or portfolio) of securities the performance of which were generally benchmarked against the general market, for that asset class, to determine the skill of the portfolio manager in stewarding the assets of the client. Thus, if the collection of assets were a combination of US shares, the fund manager may have been asked to outperform the S&P 500 index whereas, if the collection of securities were global bonds, the manager may have been tasked with outperforming the Barclays Global Aggregate Bond Index. The key was thus to invest a pool of assets, generally in an asset class of the client’s choosing or which matched the portfolio manager’s expertise. Sophistication of financial markets has meant that the collection of securities has gained significant breadth leading to a wide array of asset classes as well style and region biases. Hedge fund portfolio managers can thus be extremely flexible and customise their focus area in terms of style of security, geographical location and even other factor-based nuances.

Despite the significant array of choices mutual funds shared a commonality that was important: that the assets invested did not contain leverage. Furthermore (and specifically for single asset class funds), given the focus of a portfolio manager on a specific asset class, sector, or region, the portfolio manager’s benchmark was typically the relevant market for that subset of securities. Development of theoretical finance has provided the understanding between systematic and unsystematic risk which has been used to describe exposure to certain asset classes. Thus, an equity portfolio manager for instance, is assumed to carry systematic risk to equity (equity beta) given the nature of the invested securities. In a similar way fixed income managers possess different systematic risk (beta), related to fixed income, and the

relationship of performance between fixed income and equity beta was assumed to have a negative correlation given the drivers of performance of each asset class in relation to business cycles. Meanwhile investments in all securities, in the proportions of the market portfolio, provided complete exposure to systematic risk, within a market, and completely diversified unsystematic risk.

For an investor seeking to outperform an asset class, or with the intention of merely providing a level of absolute investment returns over the long term, the universe comprised single asset class or multi-asset managers that provided purely long exposure to the underlying asset (or collection of assets). The conception of hedge funds, by Alfred Winslow Jones in 1949, significantly altered this notion by creating a new class of fund (Agarwal & Naik, 2004). The concept allowed a hedge fund manager to have both long and short positions in securities thereby benefitting from both the upside and downside in security returns while providing the potential of lowering risk by adding varying exposure to uncorrelated or inversely correlated assets. Previously the only method of benefitting against a relative benchmark, in a security that was perceived to fall in value, was to omit this security from a portfolio thereby benefitting from the relative underweight position. Using short positions a hedge fund manager could benefit outright from the assertion that a security was overvalued.

A subtle consequence of this was the fact that hedge fund managers no longer had significant beta; in theory, should a manager have an equal weight in both long and short positions, that manager would be market-neutral and thus have no market beta. The portfolio in question would benefit from the idiosyncratic differences between individual securities rather than general market dynamics. An investor, allocating between bonds and equities, would need to treat this vehicle with caution as it would not provide purely long exposure to the individual asset class, and thus market. (Siegel, 1992).

This new investment vehicle created significant allure for both portfolio managers and investors. Portfolio managers could create more sophisticated portfolios as there were more ways to generate investment returns. The portfolio manager could also adjust the portfolio's overall level of beta, through short positions, thus negating the effect of market cycles. For an equity manager in an economic slowdown this implies the opportunity to outperform on an absolute basis even in an environment when equities,

overall, were underperforming. From an investor perspective it created a new universe of portfolio managers that could, in theory, outperform in any market environment.

In addition, hedge funds provided the added benefit of uncorrelated returns between assets which allowed for significant overall diversification by an investor. Consider for instance a portfolio of shares and bonds – in theory a share portfolio should outperform when a bond portfolio is underperforming. This provides negative correlation in normal conditions. Hedge funds, given the lack of beta, thus provide diversity by being uncorrelated to traditional asset classes. This diversification is significant as it provides better risk adjusted returns and protects against incorrect asset class positioning. More uncorrelated exposure across assets provides a better portfolio outcome through these risk adjusted returns so hedge funds provided significant benefits to investors.

The inherent lack of beta in hedge funds creates an odd quandary in terms of performance assessment. Hedge fund asset growth was significant in two decades prior to the great financial crisis in 2008 (Ibbotson, et al., 2011). Prior to the proliferation of hedge funds typical mutual fund managers were measured against relative benchmarks. This was an important consideration as it determined the success of fund managers as well as the overall fee incurred by clients. This is due to the dual structure of annual management fees and performance based fees. Thus, if a portfolio manager consistently outperformed an investment benchmark, that portfolio manager would receive an annual management fee as well as a performance fee (Ibbotson, et al., 2011).

Given the fact that benchmarks typically contained the asset in which the manager was invested, the portfolio would thus contain significant beta. Manager success, and thus incentives such as performance fees, would be influenced by the excess returns that the portfolio manager would be able to achieve over respective benchmarks. This excess return was achievable through superior security selection versus the relative benchmark.

Hedge funds, given their permissible inclusion of short exposure which reduces beta, were typically not benchmarked against a relevant asset class. For instance, an equity hedge fund portfolio manager, who constructed a market neutral portfolio, would have a long book of securities that equated to a short book and thus have zero equity beta. For this reason, it became the norm for hedge fund managers to measure themselves

against an absolute return benchmark such as an inflation or a cash plus benchmark (such as cash plus two percent) (Ibbotson, et al., 2011). Given the sophistication of hedge fund portfolios the general performance fee became 20% of outperformance above a manager's benchmark or hurdle, in addition to a typical 2% management fee (Ibbotson, et al., 2011). Given a manager's potential ability to outperform in any market environment, provide uncorrelated returns, and make use of alternative tools and techniques this fee seemed adequate to compensate a hedge fund manager.

This paper tests the hypothesis that performance is agnostic of market beta for South African hedge funds. If consistent market beta exists in hedge fund returns then it shows that the conventional wisdom that hedge funds provide uncorrelated returns with traditional asset classes is wrong. If this is the case, then the higher performance fees levied by hedge fund managers, especially when compared to mutual fund counterparts, are inappropriate. The paper "Can hedge-fund returns be replicated", by Hasanhodzic and Lo (2007), will form the basis for this paper. In that paper Hasanhodzic and Lo (2007) tested whether hedge funds contained significant beta and used the results of the study to build low-cost models to replicate hedge fund returns. The Hasanhodzic and Lo (2007) study was conducted using the TASS (Trading Advisor Selection System) database of 1610 global hedge funds of various strategy type. This dissertation is different in two key ways: it firstly tests whether there is hedge fund beta across multiple asset classes inherent in hedge fund returns from South African fund managers. This replicates the work done by Hasanhodzic and Lo (2007). Crucially, this dissertation differs from Hasanhodzic and Lo (2007) in the creation and use of clones. While Hasanhodzic and Lo (2007) attempted to create low-cost hedge fund clones that could be used instead of hedge funds, this dissertation seeks to better specify hedge fund benchmarks thereby providing a more appropriate basis for performance measurement. Thus, the focus of the clone portfolios is not whether they are investable, but rather how they help to inherently understand the returns of hedge fund managers. This will better specify hedge fund excess returns and thus allow for the creation of less expensive fee arrangements between hedge fund managers and investors.

The remainder of this dissertation is set out as follows: Chapter 2 presents the review of relevant literature; Chapter 3 looks at the data assessed while Chapter 4 contains the methodology. Chapter 5 presents the results while chapter 6 concludes the dissertation.

CHAPTER 2: LITERATURE REVIEW

Hasanhodzic and Lo (2007) test the hypothesis that hedge fund performance can be replicated by "passive, transparent, scalable, and low-cost alternatives" based on the finding that a significant fraction of hedge fund returns can be attributed to common factors relating to liquid exchange-traded instruments. This was done using a regression framework to assess the sensitivity of hedge fund returns in the TASS database of 1610 hedge funds. Returns were correlated to asset class returns to demonstrate that hedge fund returns could be considered a function of traditional asset classes. Asset class returns were derived from various indices referencing the specific asset class. For instance, corporate bond exposure was represented by the Lehman Corporate AA Intermediate Bond Index. In particular, Hasanhodzic and Lo (2007) tested hedge fund returns against the returns for the stock market, the bond market, currencies, commodities, credit, and volatility. The factors were chosen as they were able to be replicated via liquid, exchange-traded securities such as futures and forward contracts.

The fact that the asset class returns could be replicated was important as the paper attempted to replicate hedge fund returns via the creation of linear clones using actively traded instruments. The efficacy of the clones and the reported beta inherent in key hedge fund strategies belied some of the key assumptions underlying the benefits of hedge funds. Paramount of these assumptions was the fact that hedge funds provided better risk adjusted returns (Smith, et al., 2016) than traditional mutual funds and that this provided significant diversification to investors' portfolios (Asness, et al., 2001). Hasanhodzic and Lo (2007) contradicted the pervasiveness of this notion.

Importantly, if hedge funds could be replicated by low-cost vehicles, or if returns from hedge fund portfolios were merely a representation of generic beta available from typical asset classes, it brought into question the significant fees inherent in the hedge fund industry. Management fees of two percentage points and performance fees in the region of twenty percentage points is common (Ibbotson, et al., 2011) but is based on the sophistication of hedge fund strategies and the ability for those strategies to provide higher risk adjusted-returns.

In addition to an assessment of appropriate fees, due consideration also needs to be given to the appropriateness of hedge fund benchmarks. Hedge funds often use absolute return benchmarks as a means of assessing performance (Stulz, 2007). For portfolios containing limited beta, owing to short positions, absolute benchmarks were appropriate as they accurately reflected the objective of those hedge fund managers and portfolios. However, absolute return targets have become pervasive which is a concern in the context of the findings of Hasanhodzic and Lo (2007).

This concern is due to the fact that outperformance versus a stated benchmark provides the premise for the performance fee inherent in hedge fund strategies. An inappropriate benchmark provides an inadequate assessment of portfolio manager skill and can, therefore, be misleading and costly to a client. Excess cost to the client is a function of the significant outperformance of equities relative to fixed income securities (Siegel, 1992) which implies that hedge funds with equity beta would be rewarded based on the equity risk premium rather than due to management skill. This also incentivises risk-seeking behaviour from portfolio managers given the benefit of higher performance fees with relatively low downside given the fact that portfolio managers do not participate in the negative returns of clients (Ibbotson, et al., 1999).. Risk-seeking behaviour would be quelled if hedge funds were benchmarked appropriately relative to the asset class in which managers were invested.

Often complicating matters is the breadth of hedge fund strategies. Long only managers can be grouped according to a variety of factors including asset class or market cap factors (ASISA, 2018). This makes funds easy to categorise and compare. However, hedge funds vary significantly given the significant optionality inherent in hedge fund construction. This optionality comes in the form of being able to short positions in companies thereby creating varying exposure to securities. Loosely, hedge funds have been categorised according to styles such as “opportunistic”, “event-driven”, “futures and currency arbitrage”, “market timing”, and “global/macro styles” (Ibbotson, et al., 1999). Agarwal, et al. (2009) expanded this list further to 45 different strategies including popular strategies such as long-short and market neutral. The difference between the two papers provides evidence of the significant expansion of the hedge fund industry in terms of sophistication over a ten-year period and highlights the inherent complexity of hedge fund classification and comparison.

A further complication is the style drift inherent in fund managers’ portfolio construction (Brown & Harlow, 2017). Style drift is a term used to describe a shifting

of a manager's investment style over time. Thus, if a manager initially had a long bias, or focus in a specific region, this could shift over time providing for a different investment experience. Brown and Harlow (2017) document the lack of consistency in mutual fund returns given various style differentials across long-only fund managers. This issue is exacerbated with hedge funds which typically do not have a stated, strict investment philosophy (Ibbotson, et al., 1999). A classification or benchmarking approach that is able to adjust to these differences will assist investors in choosing the correct fund manager, benchmarking that manager correctly and correctly remunerating that manager based on said performance.

THE SOUTH AFRICAN HEDGE FUND INDUSTRY

The focus of this study is South African hedge fund manager performance. Novare (2017) shows the significant lag between the initial conception (1949) and the establishment of the first hedge fund in South Africa (in 1998). This was followed by the first fund of hedge funds in 2003 with regulation only truly becoming prevalent in 2007, as discussed in the following paragraphs. A fund of hedge fund refers to a hedge fund that contains other, underlying hedge funds (Boyson, 2008). There are only a few hedge fund strategies available in South Africa with significant concentration in select strategies. These strategies include: equity long/short, equity market neutral, fixed income, statistical arbitrage, volatility arbitrage, multi-strategy and commodities. Within this population of strategies 60.4% of funds were equity long-short (Novare, 2017), with 12.4% of the funds being equity market neutral and 14.1% fixed income. This significant concentration in equity based strategies, and especially directional long/short strategies, makes the South African market an intuitively reasonable place to have tested the hypothesis of this paper above given the risk premia in equities relative to other asset classes.

Novare (2017) outline changes made to the regulatory environment that has increased the burden on hedge fund managers. This change in regulation happened in 2018 with the promulgation of Board Notice 52 by the Financial Service Conduct Authority (FSCA) in South Africa (Financial Services Conduct Authority (FSCA), 2018). This is the creation of fund classes known as "Qualified Investor Hedge Funds" and "Retail Investor Hedge Funds". The class distinction allows traditional retail investors the ability to invest in retail investor hedge funds. Qualified investors, i.e. those that are sophisticate and understand the inherent risks of investing in hedge funds (Morris, 2016), may invest in either class while retail investors are unable to

invest in qualified funds. The distinction provides more access to hedge funds but does impose new regulatory requirements on hedge fund managers.

The added regulatory requirements and the fact that hedge funds make up just 1% of the savings industry in South Africa (Novare, 2017) has led to concentration in the industry with the top ten hedge funds, by size, accounting for 47.6% of the total hedge fund assets under management (AUM) in the country in 2017. This has worsened from 30% in 2015. Just twenty-two funds had an AUM of less than fifty million rand with the survey noting that fund managers require between R2.9 billion and R3.2 billion in AUM to break-even on management fee collections alone. This need for size to increase operational leverage and fund the increased regulatory burden, which includes elements like risk reporting and compliance, has led to the industry collapsing into a veritable oligopoly with a few key participants.

HEDGE FUND DATA

Given the qualified investor restriction, which reserved the use of hedge funds to high net worth individuals and institutions, hedge funds have largely been exempt from the significant reporting and disclosure required by publicly traded funds and firms (Agarwal, et al., 2013). Included in the ability to avoid public disclosure, hedge funds have made the publication of performance data for individual funds/firms voluntary thereby resulting in various biases in hedge fund performance reporting.

An initial concern is the databases themselves. Joenväärä et al. (2019) find five current, common databases used in global hedge fund research. These include BarclayHedge, EurekaHedge, Hedge Fund Research (HFR), Lipper TASS, and Morningstar. There are also two seldomly cited databases: eVestment and Preqin. Joenväärä et al. (2019) found significant breadth within these databases, and high-quality results coming from three of them (BarclayHedge, HFR and Lipper TASS) but major deficiencies were found in the tested databases including lack of fund class information, assets under management and missing data from hedge funds that self-reported in different databases at different times over an investment lifecycle. The result is significantly higher reported results in individual databases versus aggregated databases which Joenväärä et al. (2019) created. The stated difference was between 0.58% and 1.25% per year on an annualised basis. South Africa's leading hedge fund database is the Hedge News Africa publication (Dube, 2013).

Dube (2013) writes about the limited number of database providers as well as the lack of hedge funds overall. Symmetry and Peregrine Securities also develop databases with performance measures: an aggregated list provides 151 hedge funds in 2013, a fraction of what is available from global databases.

The opaqueness of hedge fund reporting, as well as the lack of performance reporting standards (Fung & Hsieh, 2000), makes it difficult for market participants and investors to formulate expectations with respect to hedge funds (Fung & Hsieh, 2004). Indices, such as those mentioned above, become the pervasive method for assessing performance and drawing conclusions with respect to hedge fund returns. However, these databases are inherently flawed due to the ability of hedge funds to self-report across database providers. The result is a host of data biases associated with hedge funds. One such bias is known as survivorship bias. Brown et al. (1992) find evidence of survivorship bias and note that positive performance persistence is reflected from a set of managers that have proven successful. In addition, the survivorship tends to favour fund managers that take on more risk. This is due to the fact that managers that take on a great deal of risk have a high probability of failure. This skew risk/reward function implies that managers that remain on performance databases must have benefitted from said risk if they are still able (and willing) to report performance. There is also a risk consideration too which results from reporting fund managers having less residual risk and thus reporting better risk-adjusted returns. Hedge funds have the ability to lever and take on diverse risk (Fung & Hsieh, 2004) which implies that risk adjusted returns can be affected even more than mutual funds (which also exhibit survivorship bias).

A form of survivorship bias is known as the self-selection which in turn leads to a common bias known as the backfill bias (Ackerman, et al., 1999) (Fung & Hsieh, 2004). The bias initially results from a hedge funds ability to self-report thus incentivising managers with outsized performance to report. The resulting backfill bias occurs with the full publication of a hedge fund's returns once it chooses to form part of a database. The bias itself falsely biases returns upwards as managers who wish to report returns typically do so after a period of outperformance. This results in a skew towards successful managers thus creating a bias in an underlying database. Ackerman et al. (1999) also find a liquidation bias that occurs for managers that stop reporting in preparation for liquidation. The results of polling and surveys show that this bias is small overall but is something to be conscious of.

Ackerman et al. (1999) finally find a “Multi-Period Sampling Bias” which strings together various biases via managers being able to choose to report over various periods. This creates elements of self-selection and survivorship biases as managers choose to enter and exit surveys when it is convenient to do so. This results in various periods covered. The paper shows that performance of the funds reported in tranches outperform by 12 basis points per month and, based on the fact that they made up one-third of the sample space, raised performance of the entire sample by three basis points per month.

HEDGE FUND FEES

Sophistication of investors and the proliferation of passive investment vehicles has led to investors becoming sensitive about various aspects of fund management (Hasanhodzic & Lo, 2007). This includes items such as position-level transparency from fund managers, a certain degree of liquidity from the asset portfolio as well as a sensitivity when it comes to fees. This is especially with respect to the fact that performance fees may in fact enthuse the incorrect behaviour and be misaligned to the objective of plan sponsors (Hasanhodzic & Lo, 2007).

A typical hedge fund fee structure comes in the form of a management and performance fee. While the performance is common at 20% management fees have ranged from 2% to the current, typical 1.5% (Ibbotson, et al., 2011). An important trend has been the criticism of fees in asset management in relation to performance from fund managers. Hayes et al. (2018) reveal a variety of well documented facts paramount of which is the fact that research conducted by the Financial Conduct Authority (FCA) of the UK reveals that cheaper active funds deliver higher return than more expensive funds in the same category. In addition, there was no clear relationship shown between fees and performance together with the fact that the asset management industry exhibited high levels of profitability with little evidence of competition from a pricing perspective. The changes themselves formed part of a wider body of research that contributes to new European regulatory requirements that will provide clearer, more transparent fee structures.

Although these regulatory changes will primarily affect mutual funds, hedge funds have also borne the brunt of higher regulatory and compliance costs as well as pressure to reduce fees (Fung et al., 2018). Fung et al. (2018) find that this has

resulted in hedge fund franchises needing to reach a “critical mass” to achieve sustainability. Interestingly, fees seem to have little to do with the overall performance of hedge funds as little evidence is found to support the hypothesis that higher fees imply better manager performance (Agarwal et al., 2009). The research shows that instead of fees managers with option-like incentive fee contracts, higher levels of managerial ownership, and the inclusion of high-water mark provisions in incentive contracts were more associated with superior performance.

HEDGE FUND PERFORMANCE

The performance of beta clones will need to be assessed in the context of actual hedge fund performance. In that regard performance assessment has provided mixed results. Ibbotson et al. (2011), in a paper that discusses hedge funds in the context of alphas, betas and costs, describe hedge fund returns of 14.3% across a database of 8,400 funds in the TASS database from January 1995 to December 2009. During this period the S&P 500 had an annualised return of 8.0% in comparison. However, as noted in the paragraph on data biases, the results were subsequently adjusted for inherent biases such as survivorship and backfill bias within the dataset. This reduced the overall returns to 7.6%, below the returns of market equities. From a different perspective, net of free returns was 11.4% with alpha of 3.0%, with beta returns of 4.6% and a fee of 3.8%.

Capocci et al. (2003) assess just 2796 individual funds (including 801 dissolved funds) in an earlier period from 1984-2000. This was done with various asset-pricing models including an extension form of Carhart’s (1997) model, combined with the Fama and French (1998), Agarwal and Naik (2000) models and an additional factor that takes into account the fact that hedge funds may invest in emerging markets. The analysis shows that 25% of individual hedge funds deliver significant positive excess returns, that most of them prefer smaller shares, and that many hedge funds invest in emerging market bonds. Of the 13 strategies tested nine out of 13 offer significantly positive excess returns.

The two papers above provide very different conclusions with respect to hedge fund performance. Papers through time tend to do this touting hedge funds as superior to mutual funds, especially from a risk-adjusted basis. Stulz (2007) finds that hedge fund performance can vary drastically and is very much dependent on a number of factors.

Initial evidence in the paper reveals that hedge fund returns were in excess of mutual fund returns and the market over the assessment period from 1994 to 2006. But this was an extremely lucrative time to be a hedge fund manager given the industry assets under management and the relative opportunities. This as the spectacular growth in hedge fund AUM took place after the year 2000. At the end of the year 2000 hedge fund assets amounted to 218 billion dollars which mushroomed into 735 billion dollars in 2005. The expansiveness of this growth created more competition in the industry and limited the opportunities available in certain strategies that benefitted from market mispricing. Apart from this, Stulz (2007) discusses the issues outlined above with respect to hedge fund data as well as the need for adjustment of hedge fund performance in the context of market returns. Another important factor is hedge funds and a selective view of risk. Hedge funds that, for instance, are short gamma in option strategies may receive steady income only to face significant liabilities should optionality move against them. This, in addition to the paragraphs above on performance, illustrate that performance of hedge funds, their measurement and their attractiveness versus traditional savings vehicles (and versus the market) is complicated and multi-faceted.

CLONING HEDGE FUND PERFORMANCE

In a seminal paper, Sharpe (1992) stated that a key interest is the exposure of an investor across key asset classes. The assessment was two-fold: to understand the amount investors had invested in various funds and their subsequent exposure to different asset classes. This could then be linked to individual securities to ascertain overall exposure. To do this a detailed analysis would need to be taken of the securities held by the fund. Sharpe (1992), however, proposed, and illustrated, how a 12 asset class factor model could be used to analyse performance of a set of open-end mutual funds. In essence this created a method for using only realised fund returns to infer the typical exposures of the fund to the asset classes.

Sharpe (1992) was instrumental in demonstrating the methodology for choosing asset classes. It was desirable that an asset class be: 1) mutually exclusive, 2) exhaustive and 3) have returns that “differ”. Practically each asset class represented a market-capitalisation weighted portfolio of securities with no security included in more than one asset class with low correlations between asset classes. Crucially, for the paper in particular, it was important that each index be able to be represented by a low-cost

index fund. The asset classes used covered bills, various flavour of bonds, mortgage-related securities and various size, factor and regional based equity indices.

The resulting fund assessment provided style analysis that could be used for mutual fund assessment. Using quadratic programming an investor could determine a fund's exposure to changes in the returns of major asset classes. This allowed for the breakdown of funds into various categories such as the growth equity fund, growth and income equity fund, small stock fund and balanced fund. The assessment also allowed the classification of funds of other asset classes which provided styles such as high-quality bond fund and convertible bond fund.

Sharpe's (1992) paper goes further to discuss performance measurement. It classifies a passive fund manager as one that provides an investment style, as highlighted by the categories presented and the asset-class mixes, while an active manager provides returns in sync with investment styles but also provides returns due to security selection in asset classes. This provides the framework for better constructing fund benchmarks which can be created by passive, low-cost index funds that are better representative of the fund manager's style. A key focus is that the resulting benchmark better represents the ideals of a high quality alternative in that it is: 1) viable as an alternative, 2) not easily beaten, 3) low in cost, and 4) identifiable before the fact.

An extension to Sharpe (1992) was proposed by Fung and Hsieh (1997). An important extension of Sharpe (1992) was to include alternative managers into the study as a way to measure the effect on managers with absolute return targets. The goal was to understand returns generated by fund managers that tended to be less correlated to traditional asset classes than typical mutual fund managers.

Crucially, the addition of these strategies/managers introduced dynamic trading strategies atypical of traditional mutual fund managers. This included exposure to short sales, leverage and the use of derivatives. In summary the paper theorised three key determinants of returns with respect to asset managers' portfolios: their trading strategies, the returns from assets in portfolio and the use of leverage. Sharpe (1992) focussed on returns of asset classes but Fung and Hsieh (1997) expanded on this to better capture the varying returns of hedge fund managers.

From a database perspective the model in Fung and Hsieh (1997) assessed the returns of 3,327 U.S. mutual funds (from Morningstar) and 409 hedge fund/CTA (commodity trading advisor) pools from a unique database. This is vast contrast to the data available in South Africa, evidenced by the Novare (2017) survey, showing the depth of the hedge fund industry in the U.S. even as early as 1997.

The results in Fung and Hsieh (1997) corroborated the initial work by Sharpe (1992): that mutual fund returns were highly correlated on the asset classes on which they were based. Meanwhile, and in contrast, hedge fund managers and CTAs generated returns that had low correlation to the return of mutual funds and standard asset classes. Further, it was evidenced that there was a great deal of performance diversity within hedge fund and CTA pools. Of the regressions conducted no single asset class was dominant while, unlike mutual funds, a substantial fraction (25%) of hedge funds are negatively correlated with the standard asset classes. In addition, in only 17% of hedge funds are the coefficients of the most significant asset class statistically greater than zero and not statistically different from one.

Fung and Hsieh (2004) went further in a paper that theorized a risk-based approach to hedge fund benchmarks. Using a seven factor asset-based style model, which was able to explain 80% of the monthly return variation in hedge funds, benchmarks were able to be created for various hedge fund strategies. This, in contrast to typical hedge fund benchmarks which amalgamated the returns of various hedge fund participants, was able to overcome significant benchmark issues such as the various data biases, sampling differences, limiting history of returns and the overall lack of transparency within the industry. The methodology was to create a benchmark made up of common risk factors which contained observable market prices. The result, crucially, created structured risk factor model that could reveal vital information about the risk profile of a hedge fund portfolio. It also assists in determining how fund managers place bets and provides insight into performance and the degree of fund manager skill. This also aids in the mitigation of the lack of transparency.

Agarwal and Naik (2004) used the methodology developed by Sharpe (1992), and used by other researchers, to again test the return framework for hedge funds. The aim of the study was to characterize the systematic risk exposures of hedge funds using buy-and-hold and option based strategies. The optionality enshrined in the study was an important consideration as the complex nature of hedge fund strategies exposes investors to risk factors atypical of simple asset class or mutual fund

exposure. The methodology uses the same multi-factor model used by Sharpe (1992) and Fung and Hsieh (2004) but adds a conditional value-at-risk model which explicitly accounts for tail risk and optionality. In particular, the multi-factor model helped overcome the limitation of a short history of hedge fund returns allowing for an assessment of returns in different environments. Thus, the conclusion of the paper spoke to the resemblance of key hedge fund strategies to certain option positions (in particular short option positions) as well as the fact that these strategies often bear significant tail risk that is ignored by the commonly used mean-variance framework.

The assessment of optionality and the non-linear nature of hedge funds expanded on the initial work from the likes of Sharpe (1992), Fung and Hsieh (2004). Still, the multi-factor model used typical beta factors across various asset classes and provided key insight into the returns achieved by various hedge fund strategies. For instance, the paper found that with event arbitrage strategies a significant factor loading related to the writing of an out-of-the-money (OTM) put option on the S&P 500 index. The result is intuitive, given the nature of the strategy, but is made clear from the results of the paper by Agarwal and Naik (2004). The relation to optionality and the ability to assess and characterize hedge funds in option ideology was an important distinction and provided a better understanding of the results of a dynamic trading strategy outside of a narrative that was purely based on being long or short of the asset classes available to investors and those used in the multifactor modelling.

In 2008 a Centre for Advanced Research in Finance (CARF) (Takahashi et al, 2008) paper on hedge fund replication discussed the various methods of hedge fund replication which included factor based replication. The methods discussed included a rules-based approach, factor based approach, and distribution replacing approach. A rules-based approach can be created by systematically recreating the exposure that a fund manager or strategy provides by using ETF index options. Providers include various banks and other third party providers. Although more accessible than in recent times the strategy struggles from two flaws: 1) that market participants replicate successful strategies thus eliminating alpha opportunities and 2) that creators of systematic, rule-based strategies usually have opaque trading rules which makes it difficult for investors to understand the inherent risks. The factor based approach, which is the basis of this paper, is described similarly to previous research as a method of isolating risk factors given by various asset classes and replicating them via liquid, low-cost alternatives. The paper tests various, available, hedge fund replication strategies and found them to be successful for the most part. The key risk

lies in the manager's ability to isolate risk factors and replicate them. Finally, the distribution replicating approach, does not aim to replicate the target hedge fund return on a month-to-month basis, rather, the aim is to generate returns that have the same distribution pattern as the hedge fund returns. The success of this model, over the factor based approach, appears when multiple risk factors are difficult to find – this renders a factor based approach useless. The process involves pricing the distribution of a hedge fund's payoff and replicate it through dynamic trading of tradable securities. Downsides to the model occur from estimation error in the inference of both hedge fund return distributions and the stochastic process of an investor's portfolio and reserve assets. Even when the returns are generated from known population distribution data, and parameters are estimated using simulated data, these estimated parameters can include some errors especially in the case of small samples. While the paper shied away from choosing an outright winner amongst these replication methods it did advocate for replication given the success of these strategies as well as the access to tools available currently. The paper did acknowledge that the field is a work-in-progress.

In a similar style Wallerstein et al. (2010) discussed three replication strategies and the performance of these strategies across a survey of 17 managers that offered 21 replication products. The three approaches included a factor-based approach, a dynamic trading technique to replicate pay-offs and a bottom-up approach which the authors referred to as reverse engineering. The three approaches covered are exactly the same as those covered by Takahashi et al. (2008) in the CARF paper with an important distinction: Wallerstein was published in 2010 post the financial crisis of 2008-2009 and thus in an environment in which hedge fund strategies were frowned upon (Wallerstein, et al., 2010). This, thusly meant that replication strategies too were out of favour with market participants making the outcome of the survey all the more intriguing. Of note is that the replication strategies themselves featured significant benefits versus traditional hedge funds products. Fees were lower than typical hedge funds with either a flat fee of one to two percentage points or a with a performance fee that was half of the typical two and twenty (Wallerstein, et al., 2010). The strategies were also tradable while holdings data was transparent. The results of the survey were heterogeneous in that there was little correlation between various products and hedge fund indices. This was not odd as various hedge fund replication products had stated benchmarks different from typical hedge funds and thus acted differently from typical indices. Thus, like hedge funds themselves, the fact that replication strategies replicate various strategies and types of hedge funds means that it is difficult to

compare any one solution to an index of hedge funds. Supportive of this is the fact that three products tested actually had returns that were never more than 20% against any hedge fund index. The conclusion of the paper was that hedge fund replication strategies can, indeed, deliver competitive performance relative to hedge funds.

Amenc et al. (2010) expanded on the work of Hasanhodzic and Lo (2007) performing an out of sample test on hedge fund returns. An extension to Hasanhodzic and Lo (2007) involved correcting for non-linear dependencies which often arose from the presence of dynamic trading strategies inherent in hedge fund manager performance and risk management processes. To overcome this Amenc et al. (2010) make use of various conditional factor models. One other important change was using a combination of factors for specific strategies rather than using a similar set of factors across the various hedge fund strategies. The results of the paper confirm Hasanhodzic and Lo's (2007) earlier research – that out of sample data for linear clones underperforms typical hedge fund strategies. This, again, is due to the fact that there are dynamic parts of a hedge fund manager returns that simply cannot be replicated whether on a rolling window or static basis. Having said this the clones perform admirably well with key advantages such as transparency, liquidity and, of course, a low cost relative to investing in hedge funds directly.

CHAPTER 3: DATA

In the literature review section of this study, issues were discussed with respect to data as well as the relative lack of data available both locally and globally for hedge funds. As a subset of this data, South Africa has even fewer databases as well as funds that report. Globally, popular hedge fund databases include BarclayHedge, EurekaHedge, Hedge Fund Research (HFR), Lipper TASS, and Morningstar (Joenväärä, et al., 2019). Although these databases contain thousands of hedge funds it pales in comparison to databases for listed unit trust funds. From a research perspective this imposes limitations on the ability to answer research questions. South Africa has further restrictions with data only available from 1997 and the overall number of hedge funds both reporting and in operation far smaller than global peers. The most comprehensive hedge fund database in South Africa is the HedgeNews Africa database which contains 160 active hedge funds. In comparison the available population of long only funds across asset classes is far larger as referenced by the Morningstar database.

Given the relatively small size of the hedge fund industry in South Africa it is reasonable to expect that there would be fewer database providers. This is exacerbated by the fact that hedge funds have the ability to self-report thus allowing hedge fund managers to choose whether to publish performance figures or not (Ibbotson, et al., 2011). In comparison, registered long-only funds are required to be listed and thusly publish performance figures on a monthly basis (Financial Sector Conduct Authority, 2018). The HedgeNews Africa database is the preeminent hedge fund database but has been supplemented by surveys from companies such as Peregrine Securities, Novare and the recently launched ProfileData database.

The HedgeNews database is unique in that it reports both active funds as well as funds that have since stopped reporting. The resulting database includes 412 funds across various asset and hedge fund classes, including fund of hedge funds. Active hedge funds make up just 160 of the 412 funds which provides credence to the issue of hedge fund self-reporting. The reporting itself is done on a monthly basis and hedge fund managers have full discretion as to whether to report or not. The database was created in September 1997. In addition to performance data the database publishes descriptive data such as the strategy type, fee data, minimum investment amount, redemption terms, prime broker and AUM range.

Interesting data points, crucial to the conclusion of this study, are the performance and management fees charged by hedge funds to clients. Recall from the literature review section that the typical, historic management fee charged by hedge fund companies was two and twenty: a management fee of two percentage points and a performance fee of twenty percentage points based on a hurdle rate or benchmark. The premise of this paper is that if hedge fund managers utilise more beta to outperform absolute return benchmarks (or low absolute hurdle rates) then the risk premium inherent in typical asset classes would result in undue performance fees charged to a client. The dataset reveals that the highest performance fee charged by hedge fund managers was twenty percentage points while the lowest was zero percentage points. The average performance fee was 10.5%. From a management fee perspective, the average management fee was 0.9% while the lowest management fee was zero percentage points and the highest was 2.5%, higher than the typical global fee.

A consideration of the average, minimum and maximum fee might lead to the conclusion that hedge fund fees in South Africa are reasonable in relation to global standards. However, this could belie the underlying structure of fees given how simplistic these descriptive statistics are. To provide more perspective the fee data can be broken down into tranches to better illustrate the propensity of different fees. Table 1 represents this breakdown of fees charged across the hedge fund industry encompassed in the HedgeNews Africa database.

Table 1 - Fee breakdown of funds in the HedgeNews Africa database

Management Fee (%)	0.0	0.3	0.5	0.8	1.0	1.3	1.5	1.8	2.0	2.3	2.5
Number of Funds	141	2	10	9	97	29	57	8	57	1	2
Percentage of Funds (%)	34.1	0.5	2.4	2.2	23.5	7.0	13.8	1.9	13.8	0.2	0.5
Performance Fee (%)	0.0	2.5	5.0	7.5	10.0	12.5	15.0	17.5	20.0		
Number of Funds	169	0	1	1	35	1	31	6	169		
Percentage of Funds (%)	40.9	0.0	0.2	0.2	8.5	0.2	7.5	1.5	40.9		

The data in table 1 outlines a considerably different perspective than the sample statistics considered above. If we compare table 1 to the “two and twenty” principle it is clear that South African Hedge Funds do not exhibit the typical fee framework that investors and hedge fund managers have become accustomed to globally. Evidence of this is the vast proportion of fund managers that charge no management fee whatsoever. At 34.1% it is the largest class of management fee. Second to this is the one percentage point category at 23.5% of the sample space which is half the typical management fee. The next two common fees, at exactly the same proportion, are the 1.5% class as well as the two percentage point class. A conclusion, based on the data above, could be that South African hedge fund managers choose not to charge a management fee and rather charge a performance fee. This incentivises performance and, in theory, aligns fund managers and clients in terms of the performance objective. While this may be true, it could further exacerbate the effect of fund managers using beta (or asset class risk) to outperform hurdle rates to earn fees. Although the absolute return may please a client the risk adjusted return may be compromised by over-allocating to higher risk asset classes such as high-yield bonds, property or equity.

In the context of lower than average management fees it is important to consider the performance fee charged. The table above reveals that the majority of managers do, indeed, charge the typical performance fee of twenty percentage points but that, quizzically, the same proportion of managers charge absolutely no performance fee. The other two most popular performance fees, in this sample space, where ten and

fifteen percentage points which are fractions of twenty percentage points though correlated in quantum with the typical hedge fund performance fee.

Figures 1 and 2 illustrate the data in table 1 graphically thus highlighting the conclusions raised in the prior paragraphs.

Figure 1 - Management fee breakdown across funds in the HedgeNews Africa database

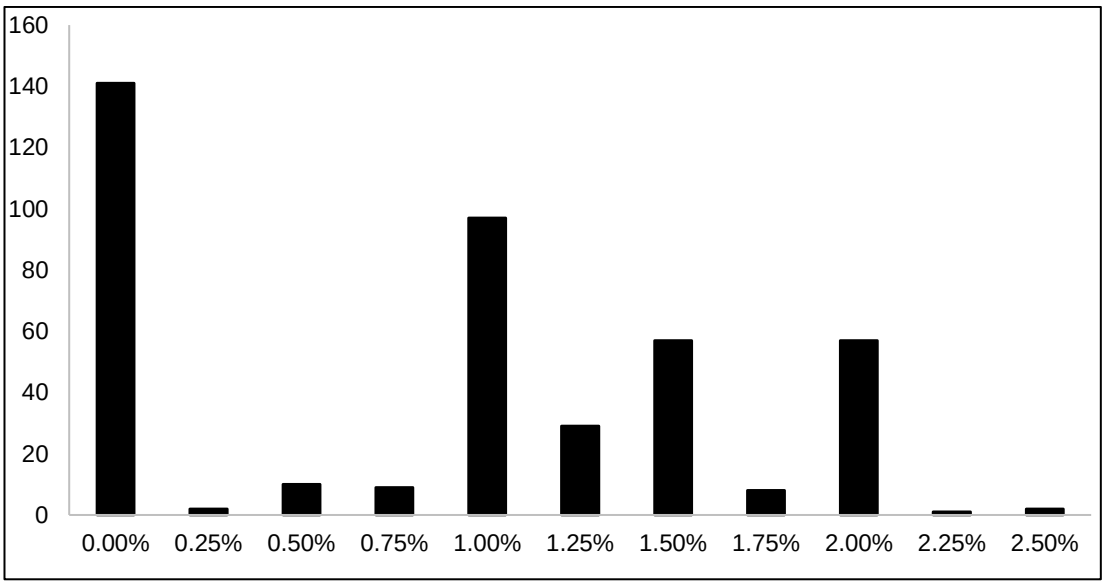
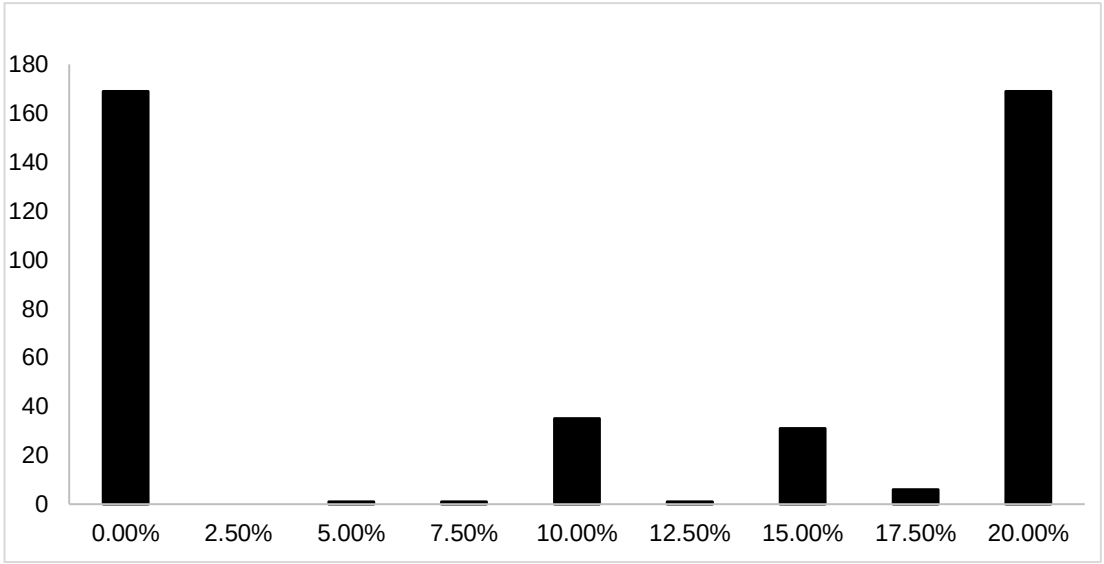


Figure 2 - Performance fee breakdown across funds in the HedgeNews Africa database



Although the zero percent management fee occurs frequently in this dataset, alternate management fees appear frequently across other tranches across the range from one percentage point to 2.5 percentage points. From a performance fee perspective, the two performance fees that stand out are zero and twenty percentage points.

Table 2 combines performance and management fees in an attempt to illustrate the correlation between the two fees. This provides the ability to understand the likelihood of fund managers charging either performance fees, management fees or some combination of both. This also provides a better framework for comparing hedge fund fees to the traditional two and twenty fee structure.

		Performance Fee							
		0.00%	**5.00%**	**7.50%**	**10.00%**	**12.00%**	**15.00%**	**17.50%**	**20.00%**
Management Fee	**0.00%**	32.2%			0.5%		1.5%		
	0.25%						0.2%	0.2%	
	0.30%								0.2%
	0.33%	1.0%							
	0.50%	0.2%			0.7%		0.2%		
	0.65%	0.2%							
	0.70%				0.5%				
	0.75%	0.2%		0.2%	0.7%		0.2%		
	1.00%	1.5%			2.7%		2.2%	1.0%	16.2%
	1.20%					0.2%			1.7%
	1.25%	1.5%	0.2%		0.5%		0.2%		2.7%
	1.30%	0.2%			0.2%		0.2%		0.2%
	1.50%	1.5%			1.2%		2.4%	0.2%	7.5%
	1.60%				0.2%				
	1.75%	0.7%							1.0%
	2.00%	1.2%			1.2%		0.2%		11.1%
	2.25%								0.2%
	2.50%	0.5%							

Table 2 - Performance and management fee intersection of hedge funds

A primary concern, based on the data from table 2, is the proportion of strategies that levy both a zero percent performance and zero percent management fee. This seems

unlikely, given the profit objective of asset and hedge fund managers, and is thus attributed to a lack of disclosure rather than a zero-rated fee. This is at odds with the initial assessment of individual performance and management fees across the fund population. Ignoring the strategies with zero-rated performance and management fees provides an illustration of how portfolio managers combine management and performance fees and provides a contrast to the traditional fee structure. A notable 11% of fund managers employ the 2% and 20% fee structure while the majority halve the management fee to just 1% while maintaining the traditional 20% performance fee. This, in theory, provides better incentives for portfolio managers as it aligns the goals of hedge fund managers and clients in terms of performance. The combinations of performance and management fees that are significant (above 1% relative to the population of 413 funds) are multiples of the traditional 2% and 20% including 2% and 0%, 1% and 10%, 1.5% and 10%, 0% and 15%, 1% and 15% as well as 1.5% and 15%. The data reveals that hedge fund companies in South Africa do not charge clients more than the traditional two and twenty but rather lower that benchmark fee in varying degrees.

The next aspect of interest, from a data perspective, is the strategy employed by fund managers in South Africa and the spread between the different strategies. Excluding fund of funds (which allocate amongst the available population) the spread of fund strategies is depicted in figure 3.

Figure 3 - South Africa hedge funds by strategy (ex-fund-of-fund)

Long/short fund managers dominate the population with the next two popular strategies being multi-strategy and market neutral funds. Agarwal et al. (2009) proposed four categories for hedge fund strategies which included: directional traders, relative value, security selection and multi-process. Each category comprised 4.6%, 16.5%, 53.5% and 25.4% of the population respectively. Agarwal et al. (2009) listed 45 different hedge fund strategies in total. Prominent strategies in the directional traders category included macro, dedicated short bias, and systematic trading strategies. Relative value contained strategies such as equity market neutral, merger arbitrage, relative value arbitrage and statistical arbitrage. Security selection included strategies such as long/short equity hedge while multi-process included strategies such as event driven and multi-strategy.

Splitting funds into these categories allows comparison and contrast between South African strategies and global compatriots. Assigning South African strategies to the various broad strategies yields the results in table 3.

Table 3 - South African hedge funds classified by strategy versus global hedge fund breakdown by strategy

Hedge Fund Strategies	Percentage of South African Hedge Funds	Classification of Hedge Fund Strategies - Agarwal et al. (2009)	Difference
Directional Traders	4.6%	24.0%	-19.4%
Relative Value	16.5%	23.0%	-6.5%
Security Selection	53.5%	42.0%	11.5%
Multi-process	25.4%	11.0%	14.4%
	100.0%	100.0%	

Security selection stands out as the largest sub-category owing to the large weight in long/short strategies. The large weight in multi-process strategies is largely due to the number of multi-strategy funds. The largest underweight in the dataset, versus the paper, is in directional traders with an underrepresentation of macro, market timing, short bias and systematic trading strategies. The result is a population that is overweight long/short strategies with a bias to directional equity strategies. Market neutral strategies (categorised as relative value) are less common in South Africa, again highlighting the prominence of directional strategies.

The overweight to directional strategies, and in particular long/short strategies, is important in the context of the study as these strategies tend to achieve excess return through asset class beta rather than nuanced alpha (Hasanhodzic & Lo, 2007). This creates the opportunity for hedge fund managers to benefit from performance based fees when benchmarked against absolute return targets.

A persistent concern in statistical data analysis are biases that affect the outcome of academic studies. Hedge fund and hedge fund reporting suffer from significant biases related to the ability to self-report. Hedge funds, unlike listed mutual funds, face less regulatory oversight given the nature of hedge fund investors. Qualified investors are

sophisticated investors that understand the risk inherent in hedge fund investing and have the capital required to meet significant minimum investment requirements. In South Africa for instance, mutual fund managers upload results to the FSCA's (Financial Sector Conduct Authority) website on a monthly basis. Results are also reported on popular databases such as Bloomberg, Morningstar and I-Net's DataStream. There are structured rules around reporting, when a manager can report and over what period. Hedge funds (until recently) did not have to lodge minimum disclosure documents (MDDs also known as fund factsheets) and could thus report on a voluntary basis. This was a result of new regulations regarding the listing and monitoring of hedge funds proposed by the Financial Services Conduct Authority of South Africa in Board Notice 52 (Financial Services Conduct Authority (FSCA), 2018). Reporting on a voluntary basis causes biases in statistical analysis as the data suffers from selected data rather than universal data. Two important biases in the context of hedge funds are the survivorship bias and the instant history bias. Both are the direct consequence of voluntary reporting.

The instant history bias (also referred to as backfill bias) is a bias that results from hedge funds having the ability to choose when to report performance. Thus, from a behavioural perspective, it is rational to assume that outperforming managers would choose to report to highlight fund performance and attract flows. Thus, hedge fund managers that choose to report, typically have outsized performance versus benchmarks and peers. This history of returns can be instantly added to databases retrospectively thus increasing overall returns for the hedge fund population. Database providers could counteract this by not allowing retrospective hedge fund reporting but the interests of database providers lie in providing as much data as possible rather than the biases inherent in that data. Jorian and Schwarz (2019) document the effect of backfill bias and highlight that hedge fund providers could eliminate a significant amount of bias from data analysis by simply stating the date that hedge funds first appeared in a data base. Traditional backfill correction involves truncating hedge fund data for the first 12,24 or 36 months to thus reduce the effect of the bias. Jorian and Schwarz find that this eliminates between 25% to 30% of the backfill bias (by truncating for 12 and 24 months respectively). Jorian and Schwarz's (2019) novel method truncates based on historic data from the add in date. The results of the paper reveal that truncating over 12/24/36 months reduces the returns from the TASS database from an average of 10.16% (over the forecast period) to 9.11%/8.82%/8.76% respectively. The approach proposed reduces the return for the population to an even lower 7.03%. The approach is concise and intuitive but will not

be used given the lack of available data with respect to the initial date that hedge funds reported in the HedgeNews Africa database. Despite the fact that truncating data only eliminates a fraction of backfill bias it is the most practical approach for reducing backfill bias given the data at hand.

Table 4 - Summary statistics from hedge fund database based on truncation window

	Full Data-Set	Cut-Offs		
		1-year	2-year	3-year
Annualised Return	19.2%	15.5%	14.1%	13.0%
Cumulative Return	3579.5%	1604.0%	1072.3%	760.0%
Years Active	20.5	19.7	18.7	17.7
Inception	30/06/1998	30/04/1999	30/04/2000	30/04/2001

Table 4 establishes the effects of the backfill basis for the dataset at hand. The full dataset begins in June 1998 and ends in December 2018. This provides 20.5 years of data. To establish the effect of the backfill bias the returns of each fund were truncated by 12, 24 or 36 months effectively eliminating the early returns for each fund. The returns across the different funds were then averaged and annualised to produce the results in the table. Eliminating one, two and three years of data shifts the inception of the entire dataset by the effective cut-offs. It is very clear from the results of the truncated data and the unaltered dataset that there is a significant difference in returns. This can be directly attributed to the effect of the instant history and the fullness of the dataset. Ward and Muller (2005) document that the first hedge funds became available just five years prior to the publication of the article implying that the HedgeNews dataset documents the returns of the earliest hedge funds available in South Africa. Given the voluntary nature of hedge fund reporting the initial performance figures in the database is evidence of an industry performing well thus willing to present returns – a clear form of the backfill bias. We can see the bias resonate even in later years as truncating returns of hedge fund providers by two and three years also presents lower returns, further evidence of the backfill bias. On an annualised basis this may differ by just two percentage points but in the context of 20 years the cumulative returns reveal the extent that this has on the statistical findings. In preparing the results of this paper all three truncation windows were used. Due to

the significant loss of data in the 24 and 36 month windows the 12 month window is used to represent results for the study.

The other notable statistical bias, in the assessment of hedge funds, is referred to as the survivorship bias (which was discussed in the Hedge Fund Fees section of the literature review of this paper). Again, the bias relates heavily to the ability for hedge funds to self-report based on limited regulatory burden. In this case hedge funds have the ability to stop reporting at any given point. From a behavioural perspective hedge funds are incentivised to stop reporting when performance is lacklustre. The general result is for database providers to remove hedge fund return series for those hedge funds that have stopped reporting. Thus the funds left generally have better returns and an upward bias from the original population. The literature review of this paper highlights the work done by Brown, et al. (1992) in proving the existence of the bias. Liang (2000) finds that the survivorship bias exceeded more than 2% in the TASS and HFR databases in a dataset that traversed the late 1990s. The ideal approach to curtailing the effect of survivorship bias is to have a database of fund returns that maintain funds that have ceased reporting. The HedgeNews Africa database has that characteristic eliminating the effect of survivorship bias. Despite this benefit the effect of the survivorship bias is outlined below by eliminating funds that have ceased reporting to provide context of the effect.

To establish the bias, the 227 available funds were reduced based on missing data. Those mandates that included missing data, after having first reported to the database, were removed. The remaining fund returns were averaged on a monthly basis and cumulative and net returns calculated. Based on the returns of the initial funds in the population 20.5 years of returns were calculated. The annualised return for the period, with the reduced dataset, was 21.8% (5566% cumulative). If we allow defunct funds and those not providing data to remain in the database the annualised returns reduce to 19.2% (3580%) cumulative. As with the backfill bias the annualised return figures seems to exist within a margin of safety, however, given the extent of the database, the cumulative return difference highlights the impact of the survivorship bias. The results section of this paper uses the database in its original form thus keeping funds that have stopped reporting within the dataset reducing the extent of the survivorship bias.

CHAPTER 4: METHODOLOGY

The confluence of ideas provided in the sections above provides the following hypotheses to be assessed:

Hedge funds do not provide beta agnostic exposure to asset classes. Given this notion hedge fund benchmarks should be reconsidered given the exposure that a portfolio manager provides based on asset class risk premia. This should also be attributed to the assessment of a manager's skill in the context of performance fees earned by managers.

The initial hypotheses relates to the asset class exposure inherent in hedge fund returns. Should that hypothesis hold it will provide the basis for better conceptualisation of hedge fund benchmarks which, in turn, should allow for better performance measurement and fair fee arrangements between hedge fund manager and investor.

The method used in presenting the results stems from two ideas: do hedge fund returns have a relationship with the returns of traditional asset classes and can that relationship be used to create benchmarks to better understand and reward hedge fund manager returns?

To understand the relationship between hedge fund returns and the asset class independent variables an ordinary least squares (OLS) multiple regression was used. This is based on the fact that a multiple regression analysis provides a framework for understanding the relationship between a set of results and multiple factors that could influence those results. Regressions tend to fit data only to a certain degree which makes an OLS regression attractive as it reduces sum of squared residuals. A typical regression can be specified by equation 1.

$$y_j = b_0 + b_1 X_{1j} + b_2 X_{2j} + \cdots + b_p X_{pj} \quad (1)$$

The regression equation attempts to ascertain the coefficients that equate the left hand side of equation to the various X variables on the right. The relationship is assumed to be linear with the coefficients of each term and the sensitivity of that factor

to the overall dependent variable on the left-hand side of the equation. An important aspect of a regression analysis is the ability to use the result as a predictive model for the dependent variable. It is this aspect of a regression analysis that will form the second section of the results relating to benchmarking and performance fees.

Conducting a regression analysis relies on a variety of assumptions chief amongst which is the fact that the relationship between the dependent and independent variables is assumed to be linear. Another important assumption is the fact that the variance of the error terms is expected to be constant for all values of the dependent variables. In addition, the error terms are assumed to be normally distributed for the process of hypothesis testing.

The intercept term is generally a constant in a regression analysis. In this iteration of the analysis the intercept serves as an important variable as it will represent the return outside of the explained return from the independent variables. In finance theory this is referred to as the excess returns or alpha. This will represent the returns provided by hedge fund managers outside what is available from typical asset classes.

Given the fact that a regression analysis uses independent variables to understand the returns of the dependent variable, the choice of independent variables is crucial. The set of independent variables selected are based on a variety of asset classes both in South Africa and offshore. Based on the data available on hedge fund strategies in South Africa it is clear that the bulk of funds have an allocation to either equities or bonds, primarily in South Africa. The primary equity index in South Africa is the FTSE/JSE All Share Index which is a market capitalisation-weighted index. Companies included in this index make up the top 99% of the total free-float market capitalisation of all listed companies on the Johannesburg Stock Exchange. Given the fact that the index is market capitalisation weighted stock weights can fluctuate based on the performance of the underlying companies. In South Africa Naspers Ltd., through its investment in Chinese based Tencent and subsequent share price appreciation, has grown to approximately 20% of the exchange. As in the Finnish example of Nokia, which reached a maximum weight of 85.5% on the MSCI Finland Index on 7 December 2000 (based on data from Bloomberg), Naspers's weight in the index is substantial relative to the weight of other shares. To adjust for this variations of the traditional FTSE/JSE All Share Index have been used to better benchmark performance for both mutual and hedge fund strategies. The most common variation is the FTSE/JSE Capped All Share Index which is also a market capitalisation

weighted index that restricts any specific stock to a maximum weight of 10%. Shares that breach this upper limit are reweighted back to 10% during quarterly index rebalances (JSE, 2014). The significant weight in Naspers makes the traditional FTSE/JSE All Share Index a poor approximation of the traditional beta inherent in South African equities. For this reason the FTSE/JSE Capped All Share Index was used as the beta associated with local equities.

South African bonds are referenced using the FTSE/JSE All Bond Index. The All Bond Index is comprised of “vanilla” bonds from across the full range of maturities in the bond market. In this context “vanilla” bond refers to a bond that pays a fixed interest rate with no unique features. The composite index contains 20 vanilla bonds ranked dually by liquidity and market capitalisation. Only conventional vanilla bonds are included, with a fixed, even if zero, semi-annual coupon. Bonds with a term of less than one year are excluded (JSE, 2013). Constituents of the index include government bonds of various maturities, parastatal bonds from South African entities, as well as corporate bonds from major South African banks. The All Bond Index will be used to facilitate asset class exposure to South African bonds.

To judge the impact of volatility as an independent variable the Chicago Board of Options Exchange (CBOE) VIX Index was used. The index is calculated from the prices of a particular basket of S&P 500 options, namely put and call options with maturities close to the target of 22 trading days and is derived without reference to a restrictive pricing model. Thus the index is constructed to be a general measure of the market’s estimate of average S&P 500 volatility over the subsequent 22 trading days (Becker, et al., 2009). To gauge the effect of currency as an independent variable the rate between the rand and the United States dollar will be used as a proxy. The dollar is an important reference currency for the world (Devereux, et al., 2010) which makes it a good proxy for beta within the realm of currency based investing.

The final independent variable will be the Bloomberg Commodity Index which will be used as a proxy for a basket of commodities. The Bloomberg Commodity Index is a broadly diversified commodity price index distributed by Bloomberg Indexes (Bloomberg Indexes, 2014). The index was originally launched in 1998 as the Dow Jones-AIG Commodity Index (DJ-AIGCI). The BCOM index tracks the prices of futures contracts on physical commodities in various commodity markets. The index comprises 23 different commodity futures amongst six sectors. No individual

commodity can make up 15% of the index while no commodity and its derivation can exceed 25% of the index. In addition, no sector can represent more than 33% of the index. Underlying commodity weights can fluctuate, however, the broad commodity categories are energy, grains, industrial metals, precious metals, soft commodities, and livestock.

In any regression analysis a key focus is the reduction of collinearity between independent variables. This refers to a linear relationship between the independent variables which results in a correlation between variables. To account and adjust for this the intended variables chosen are across different asset classes and different locations. For instance, SA equities and global equities have very little overlap, given the relative size of South African companies in the global economy. It is a similar case for South African bonds in the context of independent variables like commodities or equities. A key consideration was trying to cover as many asset classes, across various geographies, without significant overlap. Given the focus on South African hedge funds a key focus were South African asset classes. Within this there were more long short equity funds than any other. To account for the potential of offshore equity exposure a global equity benchmark, the MSCI World Index, was chosen. In the analysis below it is categorised as global equities.

An important aspect of the hedge fund data was the survivorship and instant history bias. While the survivorship bias was corrected for by maintaining dead funds, the instant history bias had to be adjusted for. In the assessment data was truncated by 12, 24 and 36 months to understand the effect of the bias as well as loss of data due to truncation. This was crucial given the relative lack of data from South African hedge fund databases. In databases like the TASS database, which featured over 1600 hedge funds, truncating by three years was still acceptable given the number of funds in the overall sample space. In South Africa a selection of just over 200 funds leaves little room for the ability to truncate a significant amount of the database to account for the instant history bias. After the choice of truncation window all funds with less than 12 months of data were removed from the study.

Even without truncating data to account for data biases there are some hedge fund strategies that simply had too few funds available to provide for data analysis. Due to this fact these strategies needed to be eliminated from the study. These included South African Managed Futures, South African Market Neutral (USD), South African Multi-Strategy (USD) and South African Special Opportunities.

The regression equation consisted of the various independent variables and the intercept in the form of equation 2.

$$E[R_{it}] = \alpha_i + \beta_{i1}E[X_{1t}] + \cdots + \beta_{iK}E[X_{iK}] \quad (2)$$

In this form the equation is the same as the general regression formula with adjustments for the alpha as the intercept term and the expected return of the various independent variables. After truncation and the subsequent elimination of funds that had less than 12 months of history, regressions were performed on every single hedge fund in the database based on years active. Thus, a fund manager with three years of performance and one with twelve years of performance were each regressed over these periods with the independent variables. The choice of independent variables forced an adjustment to the data window as the FTSE/JSE Capped All Share Index only began in February 2002. The result was a forecast window that occurred from February 2002 to December 2018. A three-year truncation forced the dataset to begin in April 2001 (from the original 1997) which implies a significant truncation of the dataset beginning in 2002. Nevertheless, funds with histories short enough were also truncated through 2002 to reduce the instant history bias in newer mandates.

After regressions across the database were completed funds were grouped according to the relevant hedge fund strategy. This included: Commodity, South African Absolute Return, South African Event Driven/Credit, South African Fixed Income, South African Long Short Equity, South African Market Neutral and Quantitative Strategies and South African Multi-Strategy funds[1]. Once grouped important regression statistics were amalgamated to provide a mean based framework for understanding the results. Other data statistics, like the mean, standard deviation, minimum and maximum values were calculated for the beta values, t-statistics, F-statistics and the adjusted R-square. This provided a framework for understanding the statistical significance of the observations. Performing individual regressions allows for filtering and assessing of individual manager results thus providing the ability to filter and hone in on specific results. Though focus is given to the average of hedge fund statistics this is to understand the usefulness of the method in a broad based

[1] It is important to note the lack of data available in some of these categories as noted in the results section under "Loss of data due to statistical biases". Fund categories such as managed futures and commodities feature small universes. Crucially it does represent the entire universe of funds but does make it difficult to make broad conclusions about an entire category in relation to the overall asset class.

fashion – in practice asset allocators and portfolio managers would more likely assess individual managers in the context of the framework.

The beta coefficients associated with the independent variables are the key statistics of focus in the assessment. Thus, while a regression output provides a number of key data points the focus is on the beta coefficients and the t-tests associated with them. The sign of the beta and the absolute size provides the understanding sought for hedge fund manager performance. For instance, should the beta associated with local equities be high and positive for equity long short managers, together with a significant t-statistic for that beta, that would lend credence to the idea that the manager is receiving significant returns from local equity returns rather than any significant alpha. For equity market neutral funds, for instance, it would be assumed that the beta coefficient for equities would be close to zero, given the offsetting positions required to achieve market neutrality. Thus, if the beta coefficient came back with a value, either positive or negative, that was significant it would colour the narrative for how hedge fund managers develop returns.

THE BENCHMARK CLONES AND THE EX-ANTE ASSESSMENT

Once the regression functions are calculated expected return formulas produced for each hedge fund, and the amalgamation of strategies, it is then possible to calculate the expected returns for hedge fund strategies given the returns of the independent variables post the assessment window. While this is an interesting observation the proposed direction is to use the regression functions to clone hedge fund returns based on the asset class relationships gleaned from the regression history. Using these functions weights for different allocations to beta factors will be used to "position" the clones in different asset classes – the positions can be both positive or negative (long or short). To do this the return from each hedge fund category is calculated as a function of returns from the regression equations. This allows for the ability to breakdown and understand the contribution to return from each independent variable by calculating it as a ratio of the expected return from the entire equation. This effectively provides weights, that sum to one, of the different asset classes based on the beta coefficients.

Using these weights as the clone/benchmark portfolio weights in the ex-ante period it is possible to calculate the return that the benchmark portfolios would achieve. This

is done at strategy level but could easily be done for the individual hedge funds to understand/clone the exposure that a fund manager is exposed to. Importantly, the exercise is done as a benchmarking tool rather than for trying to replicate hedge fund returns, thereby creating an alternative to hedge funds. Due to this it is not necessary to search for tradable versions of the underlying asset classes as the hedge funds will not be replicated in the open market. This is an important and simplifying assumption as finding tradable versions of asset classes, that can be both long and short, is a difficult task. In addition, it reduces the need to understand, calculate and account for aspects likes liquidity, trading costs and operational issues such as balancing of margin accounts.

The resulting benchmark portfolios were then used to understand the return of hedge fund managers both as a comparison and as a way to attribute hedge fund returns based on the market environment at hand. The ex-ante period contains a period of significant volatility (due to the COVID-19 pandemic) which is an important test for the ex-ante performance of the benchmark portfolios.

CHAPTER 5: RESULTS

SUMMARY STATISTICS, MARKET RETURNS AND CORRELATIONS

Table 5 sets out the initial summary statistics for the funds within the HedgeNews Africa database. The entire database of funds was used to produce the table thus returns from September 1997 to December 2018. Each category/strategy of fund was used to combine results across different fund managers with the aim of understanding the mean, standard deviation and the Sharpe ratio inherent in South African hedge funds over the period assessed. Given the fact that the database comprises a variety of funds the table also calculates the mean and standard deviation of the three aforementioned summary statistics to give a range of values over the subset.

LOSS OF DATA DUE TO STATISTICAL BIASES

Importantly, the table was broken down into three distinct regions based on the level of truncation of the original data. The data section of this paper illustrated the effect that the instant history bias could have on results creating an upward bias. However, this effect, and the subsequent truncation, needs to juxtaposed against the loss of data that could arise from a small hedge fund population.

Take for instance the largest category of hedge fund: South African Long Short Equity funds. Truncating 12 months of data leaves 71 funds in the assessment window; however, the 36-month truncation leaves just 54 funds, a loss of approximately 24% of the funds within that category. As is reasonable to assume all strategies face similar losses. This is particularly noticeable for funds that already had a small population such as the Commodity subset that falls to three funds from just five initially. The overall effect is for the population to reduce from 209 funds to 159 funds based on a 12 and 36-month truncation (a loss of 50 funds and approximately 24% of the entire population.

This again highlights the relatively small size of the South African industry relative to the rest of the world. Contrasting this to the paper by Hasanhodzic and Lo (2007), which used the TASS Live hedge fund database, the disparity is stark – for instance, the paper has 520 long short funds, 83 equity market neutral funds and 59 multi-strategy funds. This in addition to strategies that simply aren't available in South Africa such as macro, short bias and convertible arbitrage strategies. For this reason, the

focus will be on the 12-month truncation window to preserve the integrity of results based on the availability of data. While this may not be the optimal decision to limit the instant history bias the statistical analysis will be bolstered by more data. It is also important to note that the survivorship bias is still accounted for by the addition of funds that have chosen to stop reporting within the reporting window.

	12 Month Truncation							24 Month Truncation							36 Month Truncation						
Category	Sample Size	Annualised Mean (%)		Annualised SD (%)		Annualised Sharpe Ratio		Sample Size	Annualised Mean (%)		Annualised SD (%)		Annualised Sharpe Ratio		Sample Size	Annualised Mean (%)		Annualised SD (%)		Annualised Sharpe Ratio	
		Mean	SD	Mean	SD	Mean	SD		Mean	SD	Mean	SD	Mean	SD		Mean	SD	Mean	SD	Mean	SD
Commodities	5	7.5%	8.5%	9.4%	4.2%	-0.44	0.89	5	5.2%	8.1%	10.1%	4.8%	-0.57	0.74	3	12.3%	6.8%	7.4%	4.9%	0.41	0.88
South African Absolute Return	11	10.3%	2.6%	5.6%	2.4%	0.14	0.42	11	9.7%	2.3%	5.5%	2.5%	0.09	0.41	10	9.4%	2.0%	5.8%	2.5%	0.07	0.34
South African Event Driven / Credit	9	11.8%	3.7%	1.9%	2.0%	3.44	4.49	8	8.8%	5.2%	1.9%	2.1%	3.08	4.53	5	7.1%	10.1%	2.0%	1.9%	4.01	6.16
South African Fixed Income	22	11.9%	4.4%	6.8%	6.5%	0.70	1.08	20	11.2%	7.0%	7.1%	7.0%	0.68	1.74	17	8.6%	5.5%	7.5%	7.5%	0.14	0.57
South African Long Short Equity	71	8.1%	8.6%	9.8%	4.8%	0.07	1.14	62	6.0%	9.2%	9.5%	4.6%	-0.20	0.80	54	4.1%	11.2%	10.1%	4.9%	-0.35	0.96
South African Managed Futures	3	12.4%	9.6%	17.4%	5.8%	0.06	0.63	3	7.7%	10.8%	16.3%	4.9%	-0.34	0.94	3	9.0%	10.7%	13.6%	8.0%	-0.23	0.85
South African Market Neutral and Quantitative Strategies	42	7.5%	8.6%	6.6%	3.9%	-0.26	0.87	38	5.7%	8.2%	6.0%	3.3%	-0.46	0.81	36	4.4%	10.7%	5.8%	3.2%	-0.81	1.66
South African Multi-Strategy	46	7.8%	8.4%	8.8%	6.1%	-0.18	0.85	42	5.8%	9.5%	8.9%	6.2%	-0.16	1.11	31	5.9%	6.2%	9.3%	7.7%	-0.31	0.77
	209							189							159						

Table 5 - Summary statistics for HedgeNews Africa hedge funds included in sample from September 1997 to December 2018 across truncation window

AN ANALYSIS OF PAST HEDGE FUND RETURNS

Focussing on the 12-month truncation window there is a clustering of funds that exhibit similar annual returns above ten percentage points namely South African Absolute Return, South African Event Driven/Credit, South African Fixed Income, Long Short Equity and Managed Futures. The instant history bias has its largest effect within the long short and event driven categories while commodity returns are actually larger after the truncation.

The standard deviation for the mean return provides a better understanding of the range of results between managers in any given category. The average standard deviation between categories is 6.8% which is significant given the annualised return figures have a range between 7.5% and 12.4% (based on the 12-month truncation). If we again use long short equities as a base case the average manger returns 8.1% per annum while managers within just one standard deviation of this return 8.6% higher and lower. This relates to a large spectrum between fund returns. Managed futures, market neutral and multi-strategy and commodity strategies share a similar standard deviation which again illustrates significant disparity.

ASSET CLASS/INDEPENDENT VARIABLE SUMMARY STATISTICS

To understand the performance of the hedge categories it is important to understand the returns inherent in the beta environment over the same period. To do this a summary of the performance for the independent variables selected is outlined in table 6.

Table 6 - Annualised measures of independent variables September 1997 - December 2018

Statistic	USD/ZAR	Volatility Index (VIX)	MSCI World Index	Bloomberg Commodity Index	FTSE/JSE All Share Index	FTSE/JSE All Bond Index
Mean Return	5.4%	0.1%	3.4%	-2.1%	10.3%	11.2%
Standard Deviation	16.6%	75.4%	15.1%	15.9%	18.6%	8.0%
Sharpe Ratio	-0.21	-0.12	0.06	-0.29	0.08	0.30

The return associated with the US dollar and South African rand currency pair, over the long term, reflects the interest rate differential between the two currencies thereby

outlining the weakening of the rand over the long term thanks to our higher inflation and interest rates (Macdonald & Nagayasu, 2000). Importantly, in the context of the US dollar based indices, which are the MSCI World and BCOM indices, the risk-free rate used to calculate the Sharpe ratio is based on US cash which yields 2.5% on an annualised basis through the test period. Another important change from the initial subset of independent variables highlighted in the data section is the use of the FTSE/JSE All Share Index as a proxy for the FTSE/JSE Capped All Share Index which only began in February 2002.

HEDGE FUND RETURNS RELATIVE TO ASSET CLASS RETURNS

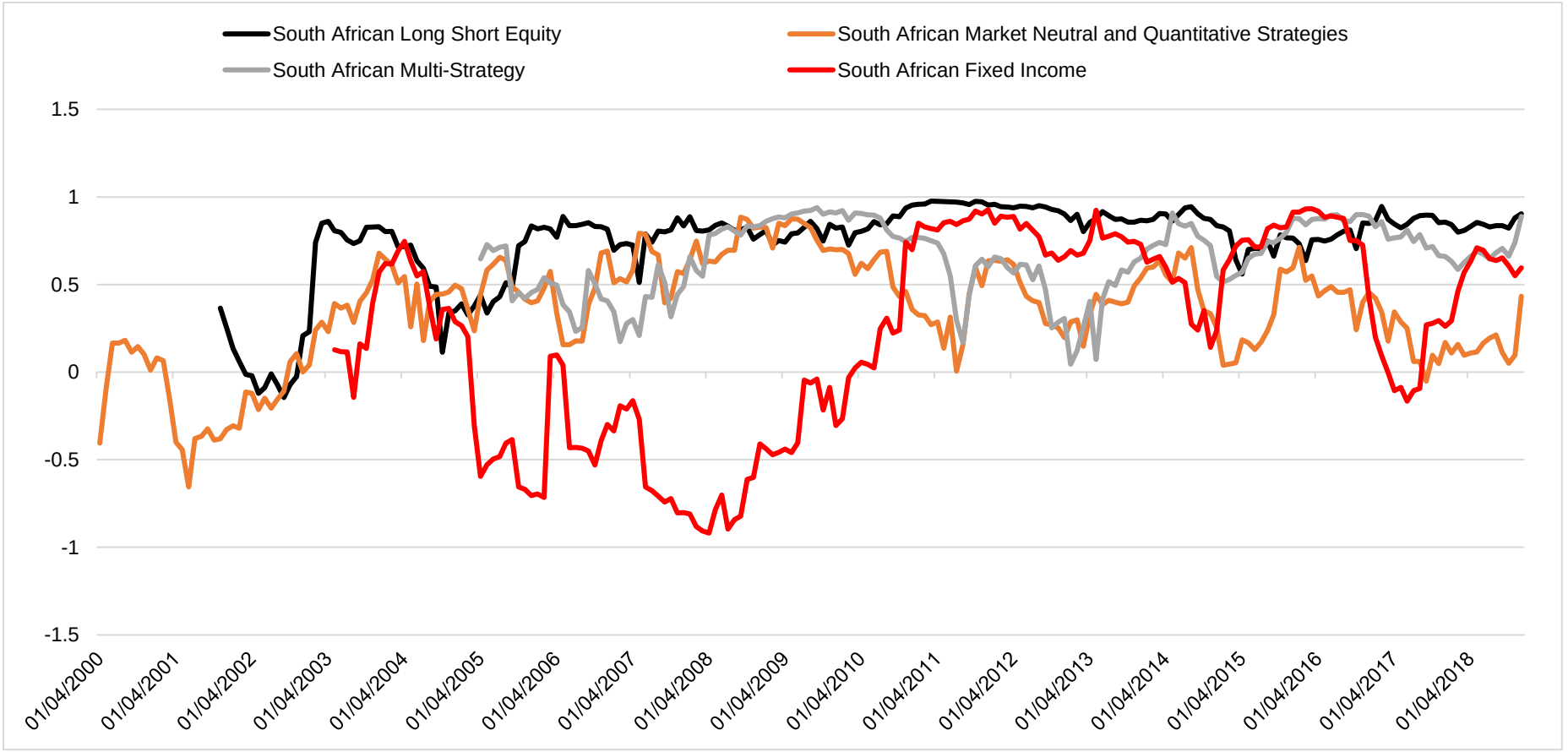
If specific hedge fund categories are considered in the context of performance versus the chosen independent variable the initial premise of this paper becomes apparent. Consider, for instance, the return of South African Long Short managers under the 12% truncation: 8.1% per annum. This is very comparable to the 10.3% mean return captured by the South African equity index. A rudimentary calculation of performance capture intones that the category captures approximately 79% of the overall returns available from equities. A similar fact is gleaned for other hedge fund categories that seem tied to a specific asset class for which there is a benchmark such as the South African fixed income category which seems to mimic the overall return for the All Bond Index quite closely. Of note, however, are the marginal Sharpe ratios associated with the index factors. This is the result of high standard deviation relative to the hedge fund categories. Both the South African long short and fixed income categories mimic the return from the beta indices but do so at a far lower standard deviation thus presenting significantly better Sharpe ratios. It is important to note that this is based on the 12-month truncation. It is clear that the Sharpe ratios reduce with the 24 and 36-month truncation though the standard deviation associated with each of the strategies remains persistently lower than that of the independent variables.

The variation of the standard deviations is reflected in column six of table 5. As for the deviation of the mean return between strategies, this provides a, better range of the deviations between managers. The deviations are consistently lower than that of the mean returns except for the fixed income strategy whose upper standard deviation rivals the deviation of the All-Bond Index. Again, for the long short mandates, imposing the upper standard of the deviation still leaves the average managers well below the standard deviation of South African equities which is an attractive quality of the dataset relative to the independent variables.

It is difficult to draw conclusions from strategies like multi-strategy, managed futures, absolute return and managed futures as these strategies could derive returns differently from different asset classes. From the perspective of an institutional or retail investor this places them in a difficult position to benchmark the underlying manager or predict the underlying return. A qualitative assessment, or due diligence, may provide better insight, but portfolio managers in those strategies generally have the ability to augment returns by investing in different asset classes when the manager sees fit. Thus the decomposition of returns via multiple regression and factoring has the ability to help better understand the underlying components of hedge fund return.

If an assumption is made that strategies such as market neutral, long short, and multi-strategy have the ability to invest in equities then the relationship between equity market returns and the performance of these strategies could provide an insight into the level of equity exposure. Figure 4 attempts to display this relationship by calculating the rolling return correlations for the three strategies with the equity market over time. The averaging across the strategies, in this case, is different from the tables above as the available fund returns are averaged monthly and correlated to SA equities. In table 5 each mandate's own annualised return, based on its period of existence, is averaged across the various strategies. A monthly rolling correlation allows for trend analysis as the correlation window is moved monthly across 12 month periods. The correlations start at different periods based on the availability of fund data with the market neutral dataset providing the initial results. Given the market neutral nature one would expect for market neutral funds to have low/no correlation with equity markets but this is not the case. The figure reveals periods of correlation that are as high as 0.8 while the population average is 0.35. There are periods where the correlation is close to and below one but this is a minority of the overall dataset.

Figure 4 – Rolling 12 month correlation of hedge fund strategies with SA Equities (the All Bond Index is used for fixed income strategies)



In theory long short funds should be more correlated to equity markets as they tend to have a net exposure that is higher than market neutral funds. This is indeed the case with the average correlation of long short funds correlation with SA equities close to 0.75. As with market neutral funds, there are periods where the correlation is as low as 0.2 but this is dominated by instances that are 0.75 and above. The underlying assumption of both equity long short and equity market neutral funds is that there should be some exposure to equities as an underlying asset class. This is not the obvious case for multi-strategy funds given the ability of the underlying fund managers to invest in various asset classes and strategies. Despite a plethora of asset classes both locally and globally the dataset reveals a 0.65 average correlation to South African equities and periods or correlation that is above 0.8 (a strong positive correlation). A similar exercise was done with the fixed income category of hedge funds but the correlation relates to the returns of the All Bond Index. The average correlation is just 0.23, largely driven by periods of low correlation from 2005 to 2010, but there are periods of high correlation over the latter part of the dataset with various instances of correlation upwards of 0.5.

The rolling correlations attempted to convey relationships between hedge fund strategies and underlying asset classes through time. However, crucially, the rolling correlation graphs alone cannot prove the relationship between hedge funds and beta. An important reason for this lies in spurious correlation. This is the ability for a dataset to mimic another, thus seeming highly correlated, but for that relationship to be coincidental rather than there being causality. While it seems unlikely in this case, given the overlap in investment universes, it could very well be the case. A different reason could be the fact that hedge fund managers simply have the ability to be invested in asset classes should the outlook be positive. Thus, a long short manager could have a higher net exposure to equities based on the prevailing environment. This could cause multi-strategy and market neutral managers to also increase net exposures thereby benefitting from beta. While managers have the ability to do this, and should for the benefit of clients, it does relate back to the premise of this paper that hedge fund benchmarking should be adaptive to this idea. The next section, decomposing the multiple regression analysis, is far better at providing a conclusion with respect to relationships and the ability of independent (beta related) variables to explain hedge fund returns.

REGRESSION ANALYSIS

Table 7 provides the results of the regression analysis in which each hedge fund was regressed against the six independent variables. The funds were then clustered into strategy groups with sample sizes for each. The key statistics presented in the table are the beta coefficient, t-statistic, upper bound for the 95% confidence level t-test as well as the lower bound. These statistics are calculated for each hedge fund and summary statistics provide the minimum, average, maximum, and standard deviation (SD) for each to provide depth of understanding with respect to the range of results within each strategy block. This is done for each independent variable thus providing a beta coefficient to better understand a hedge fund strategy's relationship with the chosen underlying asset classes. The test of fit for the beta is presented in the t-statistic while the upper and lower bound provide the minimum value of the t-statistic that validates the beta coefficient. The end of the table provides the minimum, average, maximum and standard deviation for the adjusted R-square (the goodness of fit for the entire regression) as well the F-statistic and significance level across the entire range of strategies. As mentioned, when discussing rolling correlations, a multiple regression analysis provides these goodness of fit tests for both the individual beta coefficients as well as the regression as a whole (via the adjusted R-square and the F-statistic) thus providing statistical validation rather than relying on what could be spurious correlation.

HEADLINE REGRESSION RESULTS PER STRATEGY: F-SCORE AND R-SQUARE

The intercept for each strategy represents the returns achieved outside of the underlying asset classes used as independent variables. This could be referred to as excess returns due to portfolio management or alpha. While the table provides the beta coefficients needed to understand the exposure of each hedge fund strategy (and fund) to the set of underlying asset classes, the key focus of the table are the coefficients and subsequent goodness of fit (measured by the t-statistic and the null hypothesis that the independent does not have any explanatory power over hedge fund returns).

Table 7 - Summary statistics for multivariate linear regressions of monthly returns of hedge funds in the HedgeNews Africa database from February 2002 to December 2018

Category	Sample Size	Statistic	Intercept				USD/ZAR (Currency Pair)				Capped All Share Index (South African				All Bond Index (South African Bonds)			
			Min	Mean	Max	SD	Min	Mean	Max	SD	Min	Mean	Max	SD	Min	Mean	Max	SD
Commodities	5	beta	0.00	0.01	0.02	0.01	-0.84	-0.17	0.55	0.49	-0.85	-0.08	0.35	0.46	-0.23	-0.02	0.26	0.22
		t-stat	-0.23	1.61	3.43	1.38	-2.77	-1.20	1.78	1.75	-2.96	-0.42	1.15	1.63	-1.24	-0.44	0.39	0.73
		Lower Bound	-0.02	-0.01	0.01	0.01	-1.48	-0.55	-0.11	0.54	-1.47	-0.55	-0.13	0.56	-1.73	-0.82	-0.36	0.53
		Upper Bound	0.01	0.02	0.05	0.02	-0.20	0.22	1.20	0.56	-0.24	0.38	1.42	0.63	0.16	0.79	2.24	0.90
South African Absolute Return	11	beta	0.00	0.00	0.01	0.00	-0.12	0.00	0.13	0.07	0.03	0.32	0.74	0.18	-0.27	0.10	0.28	0.15
		t-stat	-0.17	3.23	7.97	2.32	-3.77	0.21	6.03	2.39	1.36	8.69	13.28	3.59	-2.90	2.22	5.07	2.24
		Lower Bound	0.00	0.00	0.00	0.00	-0.21	-0.06	0.09	0.08	-0.01	0.25	0.60	0.16	-0.46	0.00	0.17	0.17
		Upper Bound	0.00	0.01	0.01	0.00	-0.06	0.06	0.18	0.06	0.07	0.40	0.87	0.21	-0.08	0.21	0.40	0.15
South African Event Driven / Credit	8	beta	0.00	0.01	0.01	0.00	-0.14	-0.04	0.00	0.05	-0.02	0.00	0.03	0.02	-0.06	-0.02	0.00	0.02
		t-stat	1.09	20.69	51.57	20.31	-2.07	-0.92	0.18	0.73	-0.57	0.33	1.51	0.71	-1.23	-0.30	0.35	0.48
		Lower Bound	0.00	0.01	0.01	0.00	-0.43	-0.13	-0.02	0.15	-0.30	-0.09	-0.01	0.11	-0.45	-0.16	-0.02	0.16
		Upper Bound	0.01	0.01	0.02	0.00	0.00	0.05	0.15	0.06	0.01	0.09	0.28	0.09	0.01	0.13	0.43	0.14
South African Fixed Income	20	beta	-0.02	0.00	0.02	0.01	-0.05	0.10	1.10	0.25	-0.07	0.02	0.26	0.07	-0.12	0.51	3.75	0.95
		t-stat	-1.65	4.57	18.41	4.27	-1.28	0.61	2.56	1.27	-0.90	0.32	2.35	0.83	-1.99	1.99	7.82	2.29
		Lower Bound	-0.07	0.00	0.01	0.02	-0.52	-0.11	0.04	0.14	-1.56	-0.21	0.01	0.34	-0.39	0.13	2.49	0.61
		Upper Bound	0.00	0.01	0.04	0.01	0.01	0.32	2.60	0.57	0.03	0.25	1.45	0.36	0.00	0.90	5.16	1.48
South African Long Short Equity	62	beta	-0.03	0.00	0.02	0.01	-0.56	0.08	0.46	0.19	-0.62	0.31	1.11	0.31	-0.42	0.09	0.68	0.22
		t-stat	-4.28	1.26	8.30	2.57	-2.99	0.78	5.81	1.67	-2.01	3.13	12.74	2.93	-1.62	0.47	4.40	1.12
		Lower Bound	-0.06	-0.01	0.01	0.01	-2.10	-0.20	0.25	0.34	-1.25	0.02	0.87	0.36	-2.05	-0.37	0.26	0.41
		Upper Bound	-0.01	0.01	0.02	0.01	-0.04	0.37	1.56	0.32	0.01	0.60	1.97	0.39	0.03	0.56	1.78	0.42
South African Long Short Equity (USD)	7	beta	-0.02	0.00	0.00	0.01	0.00	0.20	0.62	0.25	-0.05	0.19	0.42	0.15	-0.40	0.04	0.43	0.26
		t-stat	-3.25	-0.05	2.71	2.30	-0.04	1.50	2.92	1.14	-0.88	2.65	6.54	2.81	-1.79	0.05	1.06	1.00
		Lower Bound	-0.04	-0.01	0.00	0.02	-0.21	-0.04	0.07	0.10	-0.67	-0.08	0.29	0.33	-0.85	-0.36	-0.07	0.26
		Upper Bound	-0.01	0.00	0.01	0.01	0.13	0.43	1.17	0.43	0.07	0.45	0.76	0.24	0.06	0.44	1.38	0.49
South African Market Neutral and Quantitative Strategies	38	beta	-0.03	0.00	0.01	0.01	-0.29	0.02	0.49	0.15	-0.86	0.05	0.35	0.18	-0.31	0.01	1.31	0.29
		t-stat	-1.41	3.57	14.65	3.55	-2.78	-0.02	3.02	1.50	-2.30	1.12	6.00	1.49	-4.46	-0.58	2.13	1.33
		Lower Bound	-0.08	0.00	0.01	0.01	-0.76	-0.18	0.09	0.21	-2.13	-0.17	0.19	0.36	-2.36	-0.35	0.02	0.39
		Upper Bound	0.01	0.01	0.02	0.00	-0.02	0.22	1.73	0.31	-0.03	0.27	1.21	0.21	-0.16	0.38	3.94	0.75
South African Multi-Strategy	42	beta	-0.01	0.01	0.06	0.01	-1.79	0.03	0.78	0.33	-0.47	0.23	1.33	0.30	-1.18	0.00	0.67	0.35
		t-stat	-0.01	0.01	0.06	0.01	-1.79	0.03	0.78	0.33	-0.47	0.23	1.33	0.30	-1.18	0.00	0.67	0.35
		Lower Bound	-0.08	-0.01	0.01	0.02	-4.18	-0.31	0.45	0.68	-1.63	-0.13	0.33	0.37	-6.01	-0.59	0.30	1.07
		Upper Bound	0.00	0.02	0.20	0.03	0.00	0.37	1.48	0.34	-0.10	0.59	4.29	0.72	-0.05	0.59	4.81	0.77

Table 7 - *Continued*

Category	Sample Size	VIX Index (Volatility Index)				MSCI World (Global Equities)				Bloomberg Commodity Index				Statistic	Significance (%)			
		Min	Mean	Max	SD	Min	Mean	Max	SD	Min	Mean	Max	SD		Min	Mean	Max	SD
Commodities	5	-0.03	-0.01	0.02	0.02	-0.97	-0.13	0.45	0.52	-0.42	-0.12	0.10	0.22	Adj. R^2	0.00	0.11	0.24	0.09
		-0.65	-0.10	0.71	0.55	-1.82	-0.31	1.01	1.19	-3.53	-1.08	0.71	1.84	f-stat	1.01	1.85	2.46	0.53
		-0.17	-0.08	-0.03	0.07	-2.09	-0.73	-0.19	0.77	-0.98	-0.51	-0.19	0.32	F signficance	0.03	0.17	0.45	0.16
		0.02	0.06	0.11	0.03	0.12	0.48	1.39	0.52	-0.19	0.26	0.59	0.35					
South African Absolute Return	11	-0.01	0.00	0.01	0.01	-0.10	-0.01	0.13	0.08	-0.11	-0.02	0.06	0.06	Adj. R^2	0.08	0.69	0.93	0.22
		-1.90	-0.22	1.11	1.07	-2.12	-0.36	3.23	1.71	-4.56	-1.07	1.24	2.00	f-stat	3.35	43.87	101.87	26.34
		-0.03	-0.01	0.00	0.01	-0.25	-0.10	0.04	0.08	-0.17	-0.08	-0.02	0.06	F signficance	0.00	0.00	0.00	0.00
		0.00	0.01	0.02	0.01	0.00	0.08	0.26	0.08	-0.06	0.03	0.16	0.06					
South African Event Driven / Credit	8	-0.02	-0.01	0.00	0.01	-0.12	-0.05	0.00	0.04	-0.16	-0.03	0.02	0.06	Adj. R^2	-0.41	-0.07	0.10	0.16
		-1.49	-0.65	-0.04	0.51	-2.36	-0.98	-0.19	0.63	-1.44	-0.54	0.99	0.91	f-stat	0.43	0.97	2.51	0.70
		-0.07	-0.02	0.00	0.02	-0.41	-0.15	-0.03	0.15	-0.40	-0.10	-0.01	0.13	F signficance	0.03	0.56	0.86	0.30
		0.00	0.01	0.03	0.01	-0.01	0.06	0.25	0.09	0.01	0.05	0.11	0.04					
South African Fixed Income	20	-0.04	0.01	0.16	0.04	-0.78	-0.01	0.98	0.31	-0.66	0.03	0.29	0.18	Adj. R^2	-0.04	0.11	0.49	0.16
		-1.19	-0.07	1.17	0.68	-2.73	-0.47	1.58	1.32	-1.54	0.86	2.69	1.04	f-stat	0.64	3.23	18.40	4.40
		-0.19	-0.04	-0.01	0.05	-2.11	-0.37	-0.05	0.56	-2.31	-0.18	0.05	0.51	F signficance	0.00	0.26	0.70	0.25
		0.00	0.05	0.52	0.11	-0.09	0.34	4.07	0.89	0.01	0.24	0.99	0.26					
South African Long Short Equity	62	-0.07	0.01	0.10	0.03	-0.38	0.18	1.18	0.30	-0.47	-0.04	0.44	0.16	Adj. R^2	-0.15	0.33	0.89	0.23
		-3.84	0.29	3.37	1.27	-1.86	1.18	4.43	1.56	-2.79	-0.53	2.17	1.21	f-stat	0.65	10.77	83.60	13.87
		-0.12	-0.03	0.01	0.03	-1.20	-0.21	0.46	0.35	-1.14	-0.30	0.00	0.26	F signficance	0.00	0.08	0.69	0.17
		-0.03	0.05	0.24	0.05	0.03	0.57	2.40	0.48	-0.04	0.22	1.19	0.26					
South African Long Short Equity (USD)	7	-0.03	0.01	0.10	0.04	0.00	0.40	1.29	0.48	-0.18	-0.07	0.10	0.09	Adj. R^2	-0.08	0.32	0.54	0.20
		-1.77	0.16	1.37	1.03	-0.03	1.96	2.67	0.98	-2.15	-1.00	0.63	0.88	f-stat	0.64	9.45	22.36	8.59
		-0.07	-0.03	-0.01	0.02	-0.33	0.01	0.19	0.18	-0.72	-0.29	-0.14	0.21	F signficance	0.00	0.12	0.70	0.26
		0.01	0.06	0.26	0.09	0.28	0.78	2.38	0.84	-0.01	0.15	0.43	0.18					
South African Market Neutral and Quantitative Strategies	38	-0.05	0.00	0.08	0.02	-0.50	0.05	1.47	0.28	-0.18	-0.01	0.22	0.08	Adj. R^2	-0.20	0.14	0.70	0.19
		-2.20	-0.25	1.54	1.06	-2.92	0.09	2.98	1.13	-2.63	-0.31	2.34	1.17	f-stat	0.36	3.86	17.71	4.21
		-0.27	-0.04	0.00	0.05	-1.38	-0.26	0.05	0.30	-1.04	-0.18	0.02	0.21	F signficance	0.00	0.22	0.90	0.30
		0.00	0.04	0.42	0.07	-0.03	0.36	4.33	0.70	-0.04	0.16	1.27	0.23					
South African Multi-Strategy	42	-0.63	-0.02	0.11	0.10	-3.60	-0.02	0.58	0.62	-0.27	-0.01	0.48	0.14	Adj. R^2	-0.21	0.23	0.69	0.24
		-0.63	-0.02	0.11	0.10	-3.60	-0.02	0.58	0.62	-0.27	-0.01	0.48	0.14	f-stat	0.41	5.06	33.41	6.38
		-1.22	-0.08	0.04	0.19	-7.85	-0.52	0.08	1.23	-2.92	-0.36	0.10	0.54	F signficance	0.00	0.17	0.86	0.26
		-0.04	0.04	0.22	0.05	-0.06	0.47	2.54	0.46	-0.02	0.33	2.38	0.51					

COMMODITY HEDGE FUNDS

The commodity category is a type of hedge fund category in which it is often difficult to understand the underlying beta against which to benchmark. Commodity investing could be in the physical commodity, derivative market or in companies that derive revenues from commodities (like mining or agriculture companies). The list of available commodities is also significant from hard and soft commodities to sub-categories like base metals, precious metals, and energy (amongst others). Given the range of investment options it is unsurprising that the adjusted R-square, across an admittedly small sample of commodity hedge funds, is just 0.11 with a maximum R-square of 0.24. It is important to note that the adjusted R-square penalises the original R-square for more variables hence the relatively small figure alluding to a lack of explanatory power for the entire model. In the context of the independent variables South African equities, bonds and global equities all fail the t-test at either the upper lower bound across the mean results. Currencies, volatility and the Bloomberg Commodity index all have meaningful results which supports the overall regression having an F-statistic higher than the significance test despite the low R-square.

ABSOLUTE RETURN HEDGE FUNDS

Absolute return funds tend to try and outperform an absolute return benchmark such as cash or inflation plus a predefined percentage. To do this requires investment in a range of asset classes as the absolute return target is generally stable unlike individual asset class returns. Thus careful investment between asset classes that provide meaningful returns to assist in achieving the target is crucial. In theory the more asset classes the better as it means the ability to diversify returns. It is thus unsurprising that all independent variables are meaningful, according to the t-test, at the 95% level while the mean level for the overall regression is 0.69 – a strong result. The F-statistic is also significant at the 95% level.

FIXED INCOME HEDGE FUNDS

The next large category is South African Fixed Income Funds. A low adjusted R-square is belied by a significant F-statistic and significant t-test across all the underlying variables. However, while the t-tests pass at the 95% significance there are a number of variables that would fail at the 99% level such as volatility, global equities and local equities. The All Bond Index stands out as significantly beating its

t-statistic upper bound and would do so, also, at the 99% level. This makes intuitive sense given the strategy type.

LONG/SHORT EQUITY HEDGE FUNDS

The largest dataset is the collection of South African Long Short Equity managers. A significant F-statistic is supported by a better adjusted R-square than for fixed income managers. While 0.33 is not significantly large the distribution of R-squares has a standard deviation of 0.23 and a maximum value of 0.89 reflecting a host of funds that do have significant results. The beta coefficients are all significant apart from the All Bond Index while local and global equities stand out as large contributors to overall performance. This makes intuitive sense. The other category of manager are long short equity funds with a USD pricing currency. While there are a small number of them the overall regression significance is similar to the rand based long short managers. Key variables include local and global equity as well as currencies which is reasonable given US dollar nature of the mandates.

MARKET NEUTRAL HEDGE FUNDS

Market neutral managers typically have a neutral exposure to an asset class by offsetting long and short positions thus providing a net exposure of zero. Thus returns shouldn't be based on an asset class but rather the intercept/alpha that the manager can generate. Ironically the beta associated with the intercept term is zero while the test itself is significant at the 95% level. A host of asset classes including bonds, local equities and volatility have significant t-tests but the overall mean adjusted R-square is low at 0.14. Max adjusted R-square is 0.7, a much better fit, but the standard deviation is rather low to expect that to be consistent outcome in the distribution.

MULTI-STRATEGY HEDGE FUNDS

Multi-strategy funds are another type of strategy that is difficult to conceptually associate with a specific asset class given the number of underlying strategies and asset classes that could be used to derive a return. This is consistent with the regression output which highlights significant t-tests for the currency variable, South African equities, and volatility. It is interesting to note that South African bonds and global equities failed to beat the null hypothesis despite being asset classes that could be at the disposal of multi-strategy managers. The overall regression has a significant F-statistic though the independent variables that failed to be significant reduced the adjusted R-square to just 0.23. Despite this the distribution does have a standard

deviation of 0.24 and a maximum value of 0.69 so there are strategies that better fit the independent variable used.

The overall results of the regression assessment are largely positive both for the t-statistics on the underlying variables as well as the F-statistics on the overall regression. The assessment of goodness of fit via R-Square is generally a difficult hurdle to overcome, given the sheer number of asset classes available to hedge fund managers. Nevertheless, strategies relating to specific asset classes, such as equities, featured reasonably positive R-squares and significant independent variables. The tests for these individual strategies could limit the number of variables or even add a different set of variables which could yield better results. The aim of this paper was to maintain a broad-based set of independent variables rather than try to augment the asset classes to suit the hedge fund strategies at hand.

REGRESSION RESULTS PER STRATEGY: BETA COEFFICIENTS

The intercept for each hedge fund strategy provides insight into the excess returns/alpha that hedge fund strategies and managers provide. All t-tests for the significance of the coefficients are significant at the 95% level. While the intercepts may seem small, and clustered around zero, it is important to note that the intercepts are additive in the expected return formula. Figure 5 breaks the range of intercepts down into percentage format with the spectrum extending from -0.5% to 0.9%. In all cases, bar South African Long Short (USD), alpha is positive thereby alluding to hedge fund managers adding returns above the mere independent variables. One crucial aspect of this to understand is the fact that the alpha generated has much to do with how well the model is specific. Thus, for strategies such as commodities and event driven/credit, the lack of representative independent variables (and thus a low goodness of fit via adjusted R-square) could give a spuriously high alpha. For mandates less specific, like absolute return, long short, and fixed income the alpha represents the return outside a better specified model**.**

Figure 5 - Alpha/intercept breakdown of South African hedge fund universe per strategy

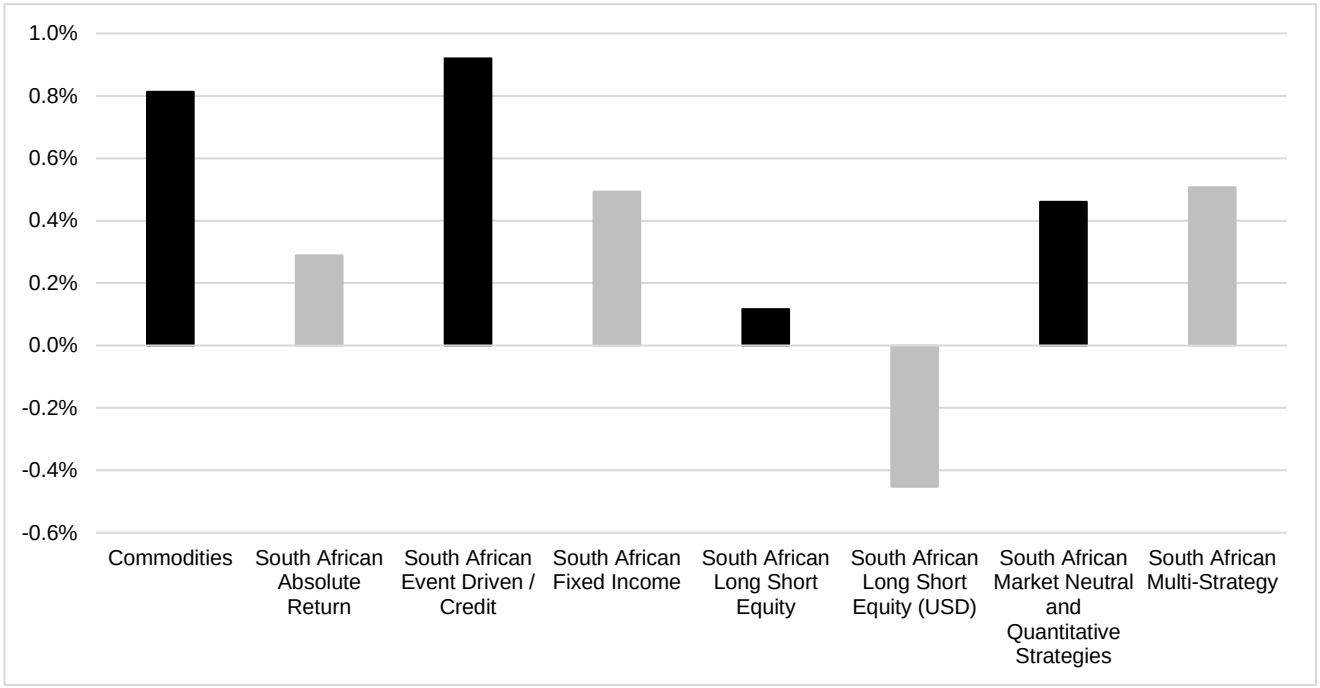


Figure 6 - Beta coefficients for hedge fund strategies based on regression analysis

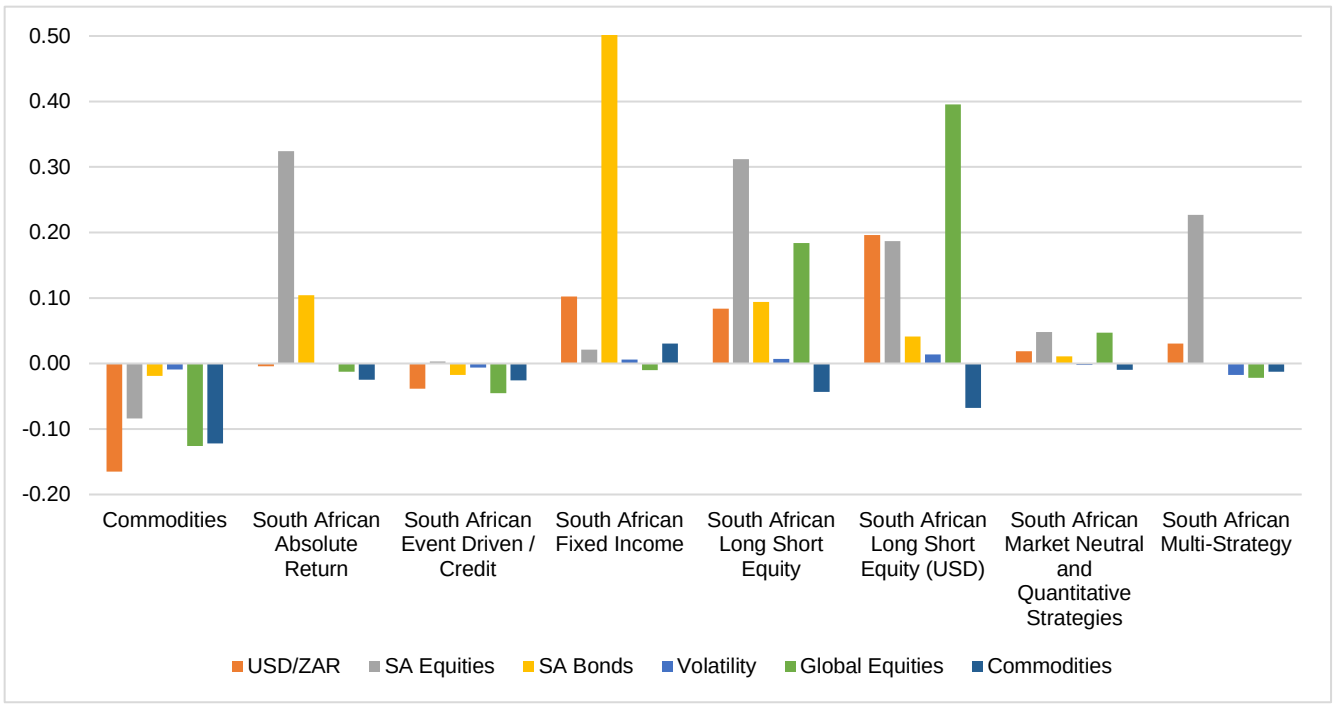


Figure 6 provides a breakdown of the betas associated with the different hedge fund strategies reflected in table 7. The regression table made it clear that there were a number of strategies that had significant test statistics for the various independent variables; the strength of these relationships is reflected in figure 6. Thus, the y-axis in the figure reflects the beta coefficient while each independent variable is listed. The range of betas extends from -0.2 to 0.5. All strategies that have less than five funds were removed from the assessment. This included South African Managed Futures, South African Market Neutral and Quantitative Strategies (USD), South African Multi-Strategy (USD) as well as South African Special Opportunities.

COMMODITY HEDGE FUNDS

Commodities have negative exposure to all underlying asset classes with a marginally positive coefficient with respect to alpha. A negative relationship with bonds and the US dollar, a rand currency pair is intuitive given that a weaker dollar and bullish environment for growth (a weaker environment for yields) are both positive for commodity prices. However, the negative beta associated with the Bloomberg commodity index is at odds with the perception of the overall strategy. Again, this could be because commodity managers invest in commodities using various tools but this is, again, at odds with the negative exposure to SA equities which generally carry a high degree of resource exposure. Commodity managers could have a market neutral or a short bias to commodities, though this seems unlikely. A small dataset of just five funds provides limited benefit as these mandate could all be idiosyncratic.

ABSOLUTE RETURN HEDGE FUNDS

South African Absolute Return funds have a large beta component related to SA equities and another relating to SA bonds. This is realistic given the mandate of these strategies to achieve an absolute return over time. In a similar way multi-strategy funds have exposure to SA equities as its largest component but limited exposure to other asset classes. Multi-strategy managers have the ability to make use of a variety of asset classes but there is little in the way of asset class diversification from the regression with marginal negative beta coefficients for volatility, global equities and commodities. The other positive exposure comes from currency but is outweighed by the beta associated with equities.

FIXED INCOME AND LONG/SHORT EQUITY

The three strategies linked to an underlying asset class are the fixed income, equity long short and market neutral. Focussing on long short and fixed income, given the assumption of a net exposure to each respective asset class, there is clear beta exposure to both SA equities and SA bonds from both long short and fixed income managers respectively. This implies beta exposure from underlying managers. The beta coefficient relating to bonds is 0.5 which implies a strong correlation in fixed income hedge fund returns to the overall performance of the bond market. Long short managers have more nuanced returns stemming from a beta component associated with global equities. The combination of betas associated with local and global equities is close to the overall exposure that fixed income managers receive from the bond index. Long short managers also reflect correlations with currency as well as SA bonds. While this could be spurious it could reflect the ability of hedge fund managers to invest across asset classes thus implying that there could be a subset of long short managers that have net exposure to offshore assets or even local bonds. South African Long Short (USD) managers price funds in US dollars but the underlying exposure of managers are unknown. The regression reveals that the majority of the underlying exposure comes from global equities which is congruent with dollar based nature of the funds. There is also exposure to SA equities and currencies which implies that managers are using a mix of global and local equities to create a long short mandate with a core focus on global equities. It is this result that exhibits the strength of this assessment. Without a qualitative assessment of the manager (or set of managers) it would be difficult to assume or categorise this type of hedge fund strategy. This assessment allows for better understanding of the underlying risk factors. While this paper uses this information to better benchmark hedge funds the paper by Hasanhodzic and Lo (2007) use the results to create hedge fund clones to create cheap, ETF based hedge fund exposure. The results could also help asset allocators better understand the hedge fund universe thus allowing for better investment decisions in an opaque industry.

MARKET NEUTRAL HEDGE FUNDS

The final strategy worth noting is the South African Market Neutral set of funds. As the name implies investors would expect limited net exposure to any one asset class and this is indeed the case with marginal net exposure to South African and Global Equities. The result validates the overall exposure that hedge fund managers in this category should have and is an important reason for why a regression assessment of

returns is better than the rolling correlation assessment in figure 4 of this results section.

ASSET CLASS CONTRIBUTION TO HEDGE FUND RETURNS

Table 8 - Contribution to hedge fund returns from traditional asset classes based on regression equation

Category Description	Sample Size	Avg. E[R] (%)	Average of percentage contribution of factors to total expected return (%)						
			Alpha	USD ZAR	SA Equities	SA Bonds	Volatility	Global Equities	Com-modities
Commodities	5	7.3	1.5	-31.0	-15.7	-3.6	-1.7	-23.6	-22.9
South African Absolute Return	11	10.1	0.6	-0.9	68.5	22.0	-0.1	-2.6	-5.2
South African Event Driven / Credit	8	11.9	6.3	-26.4	2.0	-12.0	-4.4	-31.2	-17.6
South African Fixed Income	20	12.0	0.7	14.9	3.1	74.5	0.9	-1.5	4.4
South African Long Short Equity	62	7.2	0.2	11.5	43.0	13.0	1.0	25.4	-6.0
South African Long Short Equity (USD)	7	0.4	-0.5	21.7	20.6	4.5	1.5	43.6	-7.5
South African Market Neutral and Quantitative Strategies	38	6.9	3.3	13.2	33.8	7.8	-1.6	33.4	-7.0
South African Multi-Strategy	42	8.2	1.6	9.7	72.2	0.0	-5.5	-7.0	-3.9
Asset Class Returns	-	-	-	3.3	15.6	9.0	-1.3	5.8	-2.7

Table 8 estimates the return contribution from each asset class based on the beta coefficient and the expected returns from the different asset classes over the forecast period using equation 3.

$$E[R_{it}] = \alpha_i + \beta_{i1}E[RiskFactor_{1t}] + \cdots + \beta_{iK}E[RiskFactor_{Kt}] \quad (3)$$

The beta returns in the last row of the table shed light on the relationships between certain strategies and the associated beta coefficients. For instance, commodity funds had a negative beta associated with the returns of the Bloomberg Commodity Index. Understanding that the overall exposure to commodities was negative over the forecast period helps to understand that the relationship is actually positive in nature.

Another important factor is the overall returns of SA equities and bonds which performed the best amongst the range of asset classes. This fact scales the return contribution associated with these asset classes for each range of fund. Thus, a small beta coefficient could still relate to a large component of returns coming from these respective asset classes. The effect scales the beta associated with the All Bond Index on fixed income funds to 82%. A similar effect takes place for all strategies that had exposure to equities which includes South African Absolute Return, Long Short Equity (and USD), Market Neutral and Multi-Strategy. The effect also scales up SA equities in the commodity subset of funds which could imply that managers are also getting commodity exposure via mining companies in South Africa as perceived.

ASSESSING EX-ANTE PERFORMANCE OF HEDGE FUND CLONES/BENCHMARKS TO HEDGE FUND STRATEGIES

The assessment window of our results covers a period from 1997 to 2018. The ex-ante results define portfolios based on the hedge fund beta coefficients and market returns during the forecast window. The weight allocation was then used to construct a portfolio for each strategy which could be compared to the collection of returns for hedge funds for the HedgeNews Africa database post the initial time period. The period tested begins in January 2019 and ends in June 2020. The forecast period is an interesting one given the significant market gyrations from a the global COVID-19 pandemic that shook the world in early 2020. The result is a market environment that has been significantly volatile both on the upside and downside. Figure 7 and table 9 highlight the returns over this period.

THE MARKET ENVIRONMENT IN THE EX-ANTE PERIOD

Figure 7 - Return environment in the ex-ante window (January 2019 - June 2020)

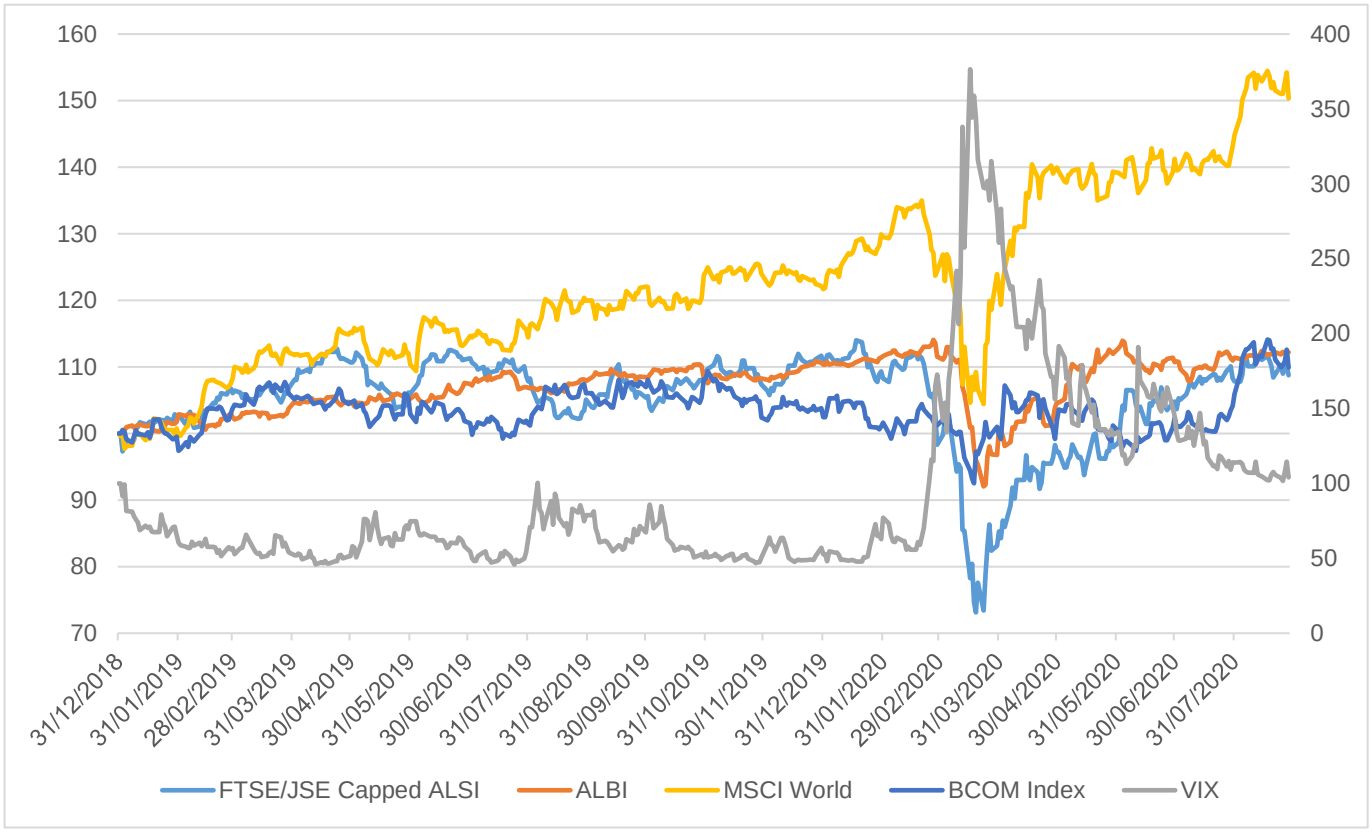


Table 9 - Return of asset classes in ex-ante period broken down into key segments

Period Narrative:	Test to Peak	Peak to Trough	Trough to Q2	Peak to Q2
Indices	Returns (%) 31/12/2018 - 14/02/2020	Returns (%) 14/02/2020 - 23/03/2020	Returns (%) 23/03/2020 - 30/06/2020	Returns (%) 14/02/2020 - 30/06/2021
FTSE/JSE Capped ALSI	11.4	-34.1	42.8	-5.9
All Bond Index	12.4	-18.1	20.3	-1.5
VIX Index	-46.2	350.2	-50.6	122.4
MSCI World Index	29.1	-34.1	37.4	-9.4
Bloomberg Commodity Index	-1.7	-17.7	4.8	-13.8

Table 9 is reflective of the three distinct periods that characterise the post assessment period. From the end of 2018 to February 2020 there was a period of general bullishness – the extension of the bull market that began after the Great Financial Crisis (GFC). While there are a myriad of reasons for why returns developed as they did during this period, the key is the market peak to trough from February 14th to March 23rd. The period is reflective of a market shock caused by the COVID-19 pandemic which caused the majority of countries around the world to shut-down and limit movement to curb the spread of the virus. The knock-on effects of this were virtually zero demand, catastrophic unemployment and significantly weaker global markets. The effect was extremely widespread and nuanced. Consider for example the flagging oil price which was the result of a lack of demand given the lack of movement. Both the graph and table reflect this shock and both reveal widespread stress across all the asset classes tested. The VIX index, a gauge of volatility, spiked significantly reflecting the surge in an uncertainty.

Significant liquidity from central banks, immense fiscal intervention from national treasuries and a seeming peak in virus cases and deaths has allowed global financial markets to rebound significantly since March hence the recovery reflected in the graph and table. Trough to quarter to and peak to quarter to returns in the table reveal both a significant rebound and the fact that financial markets were effectively to, or nearly back to, the peak level seen early in 2020.

The narrative is important as it truly colours the effect of the ex-ante results from the regression in comparison to the live hedge fund returns. A period of significant volatility, amidst an event like a global pandemic, should cause very different portfolio management decisions than would the result of a fixed weight regression based on the past.

SUMMARY PERFORMANCE OF EX-ANTE CLONES/BENCHMARKS VERSUS HEDGE FUND STRATEGIES

Figure 8 – Comparative annualised returns of hedge fund strategies and linear clones January 2019 to June 2020

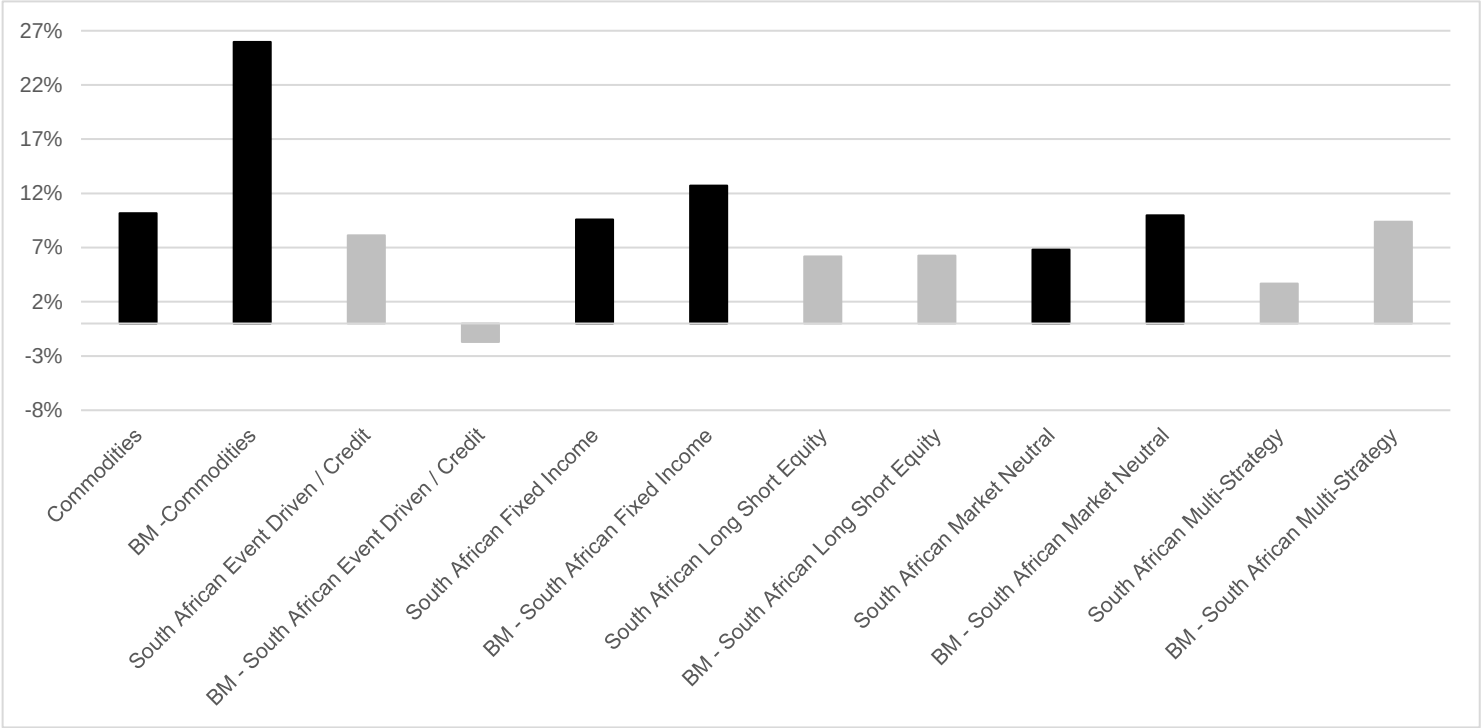


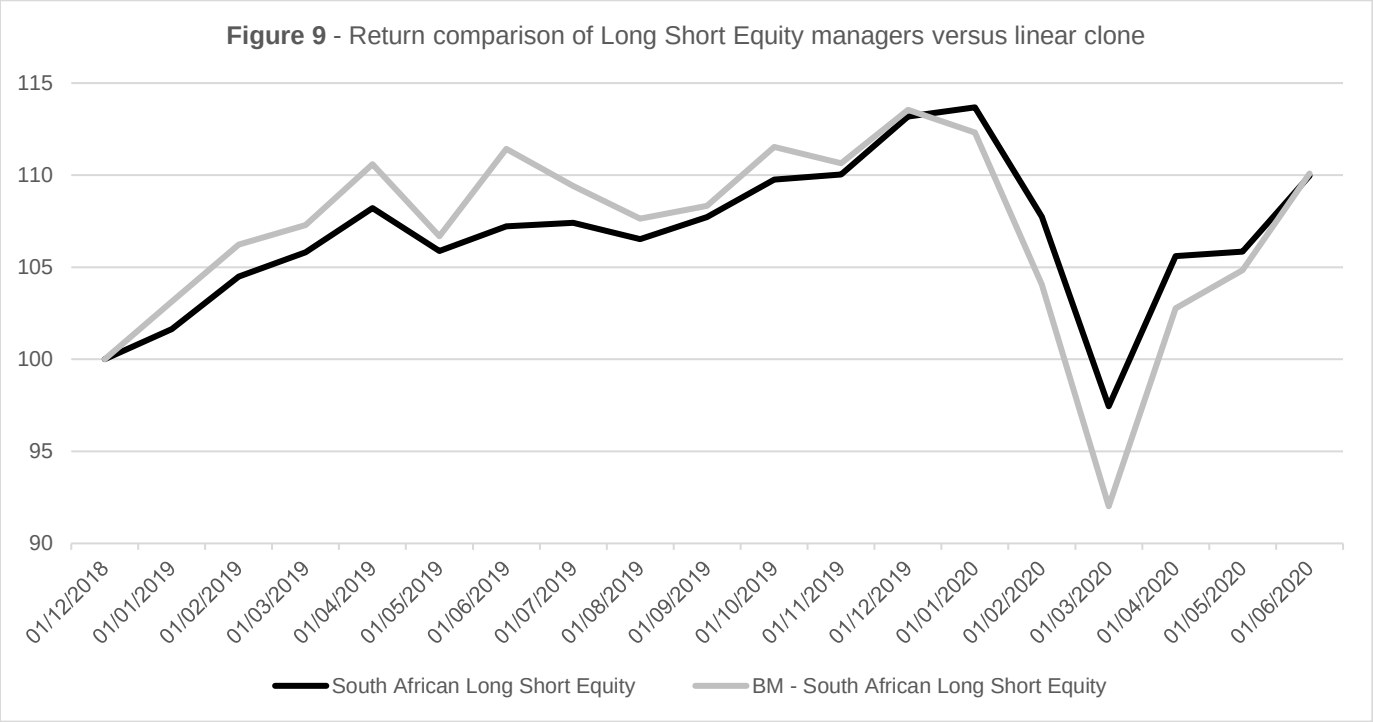
Figure 8 reflects the annualised cumulative performance for the regression based clones (ex-ante) as well as the returns for the hedge fund categories over the same period. Based on the original regression absolute return and equity long short USD funds were removed as the database no longer includes funds reporting under those categories during that assessment period.

The largest return disparities between the live hedge fund strategies and the clones are for the commodity and event driven/credit strategy. Of note is that the event driven strategy is the only benchmark clone that underperforms its relevant strategy.

Between fixed income, long short equity, market neutral and multi-strategy there is a range of variation of between zero and six percentage points – an admirable range given the significant volatility inherent in the period.

PERFORMANCE OF EX-ANTE CLONES/BENCHMARKS TO SELECT STRATEGIES

Figure 9 - Return comparison of Long Short Equity managers versus linear clone



A depiction like figure 7 hides the fluctuations in return throughout the period. To better understand the performance of the benchmark clones through time figure 9 was used to understand the performance between long short managers and the subsequent clone. Amongst all clones and the live hedge fund data the long short category is best mimicked by the clone strategy effectively returning the same return over an 18-month period. Crucially, the two strategies are in lock-step for the majority of the test period. Interestingly, long short fund managers performed better during the peak of the crisis. Given the nature of the clone this is to be expected (and appreciated) as fund managers should outperform in periods which benefit active fund management. The clone merely maintains its exposure regardless of the market environment. So significant has this period been in terms of volatility that the clone outperformed in the bullish market environment post March, outperforming the average fund manager.

Considering two more iterations of this assessment the following two figures depict the return of fixed income and multi-strategy managers.

Figure 10 - Return comparison of fixed income managers with linear clone

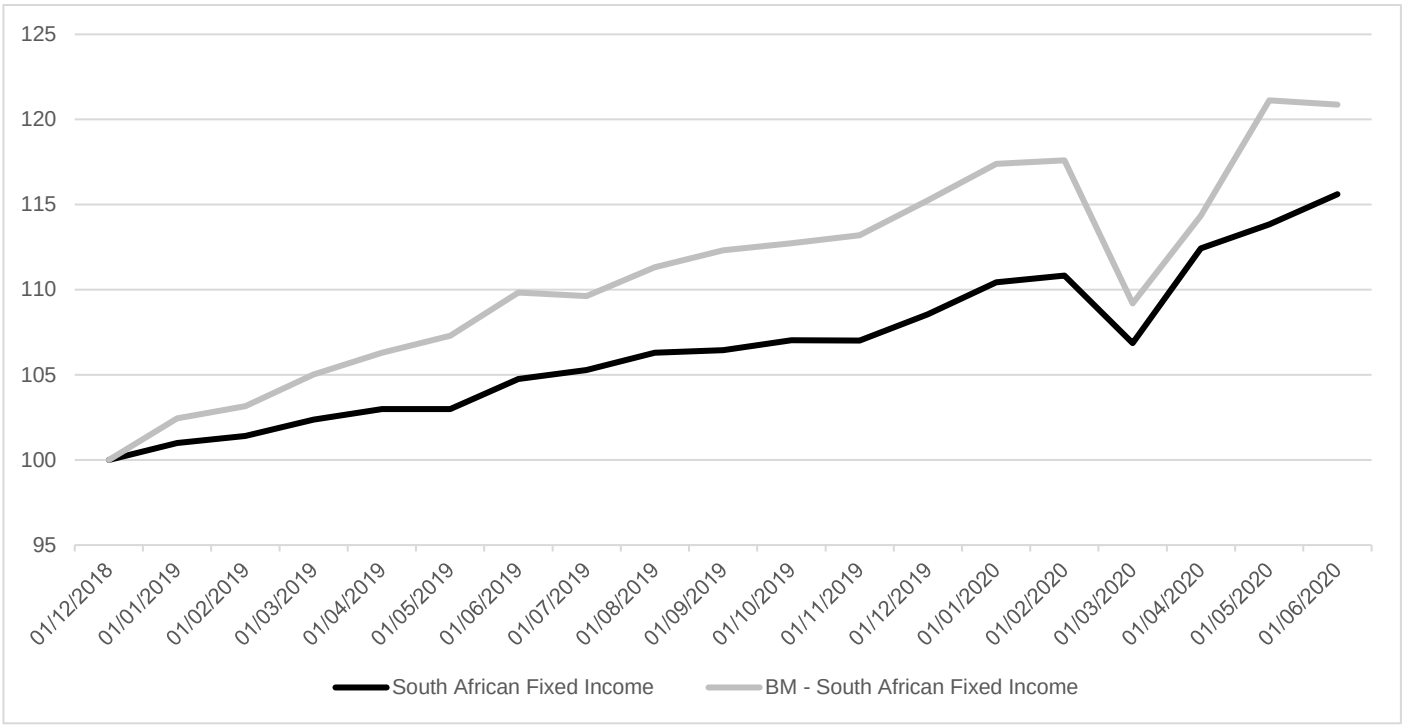
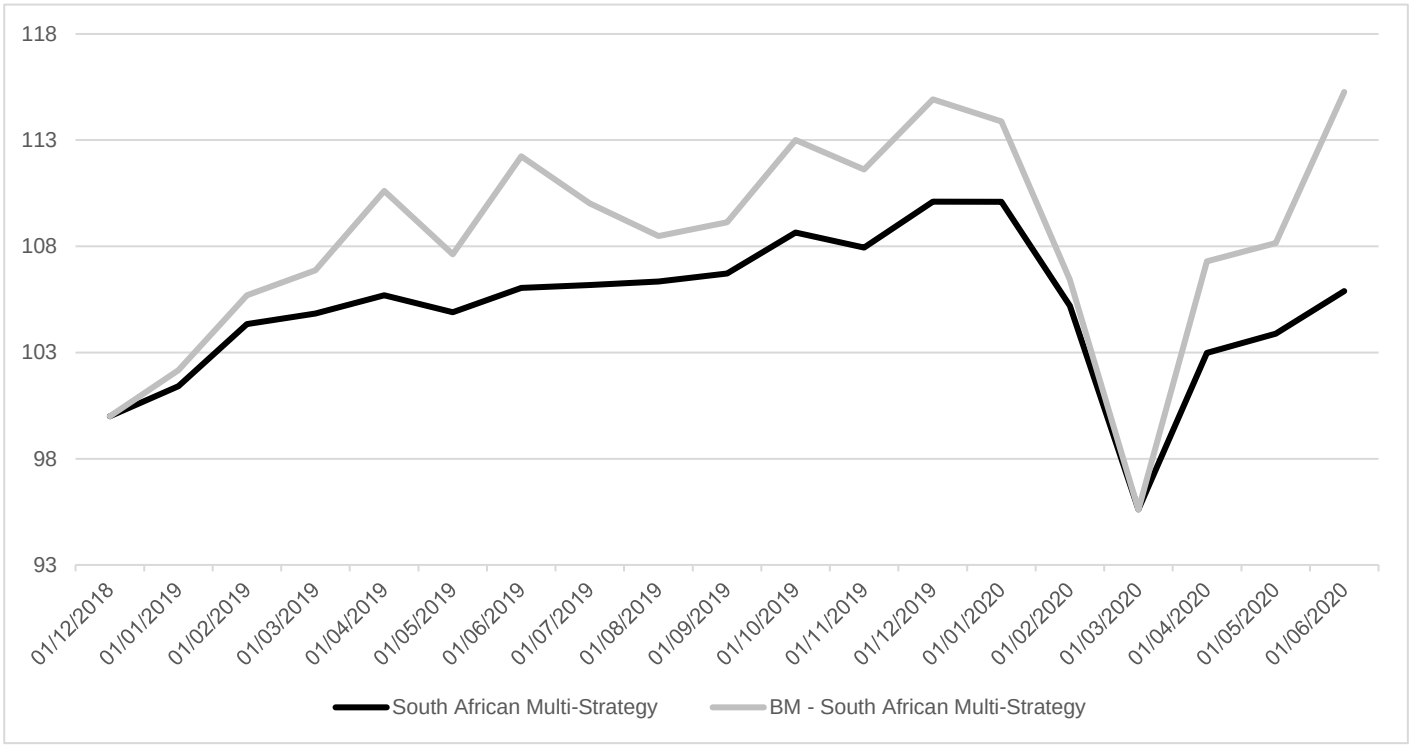


Figure 11 - Return comparison on multi-strategy managers versus linear clone



While both strategies outperform the average fund manager this is not the key focus of the assessment. The general shape and exposure seems similar in both figure 10 and 11 – it merely seems like the clones take on more risk. This may be understandable given the period of significant market volatility during the peak of the COVID crisis which forced both clones back down towards the average fund manager. Again, in the bullish environment, fund managers are left behind by the clones but this could be due to reduced risk taking by fund managers – an active view that could result in outperformance of the clone should financial markets face a downturn.

CHAPTER 6: CONCLUSION

INITIAL HYPOTHESES

The initial hypotheses of this paper relates to the asset class exposure inherent in hedge fund returns. Should that hypothesis hold it will provide the basis for better conceptualisation of hedge fund benchmarks which, in turn, should allow for better performance measurement and fair fee arrangements between hedge fund manager and investor.

DO HEDGE FUNDS RETURNS CONTAIN ASSET CLASS CORRELATION – A SUMMARY OF REGRESSION RESULTS

To that end various significant t-tests outline the fact that there is varying degrees of beta exposure inherent in hedge fund returns. While this should be expected, given that hedge fund managers allocate to the asset classes tested, it is an important consideration in understanding how benchmarks and fees are selected for hedge fund managers.

In using the beta coefficients to understand the contribution to return from different assets it became clear that there were persistent, statistically significant exposure that should be reflected in the way we allocate and remunerate hedge fund managers. Considering this in conjunction with the fact that certain asset classes have significantly outperformed cash, it becomes important to reward managers for significant generation of alpha rather than for the returns associated with cash. For cash or absolute return benchmarks mere exposure to higher yielding asset classes could result in significant outperformance and thus performance fees.

OUT-OF-SAMPLE PERFORMANCE OF CLONES/BENCHMARKS

The out-of-sample test outperformed the average underlying fund manager in most cases. While this may seem like an attractive takeaway it is not the lens from which the result should be viewed. Rather, the fact that the out-of-sample returns mimicked the fund manager returns adequately is crucial. It lends credence to the fact that the strategy can provide a strategic asset allocation benchmark that can be used to understand, quantify and reward manager performance.

Clearly the ex-ante period is significant, covering a bear market and one of the worst periods of economic performance since World War II. For the clone benchmarks to mimic returns in a highly uncertain period implies an ability to do so better in stable

market environments. From a different perspective, the difference in returns between the benchmark portfolios and the fund managers provides commentary and narrative on the wager that fund managers place in different market environments. Consider the outperformance of the benchmark portfolio for long short equity funds leading into the COVID crisis and the subsequent underperformance of the benchmark, in the crisis. It relates to fund managers reducing the risk that investors would have been accustomed to in prior years. The subsequent outperformance of the benchmark portfolio is vindication of that view and should be rewarded. In the bullish period post March 2020 the benchmark portfolio outperformed which should again raise questions from investors as to the relative wagers that portfolio managers are making between asset classes.

BENCHMARKING AND ATTRIBUTING HEDGE FUND MANAGER RETURNS

Thus, the results of this paper have significance in two distinct areas: in the ability to benchmark returns as well as for conceptual attribution of hedge fund manager performance. From a benchmark perspective, it allows asset allocators to better benchmark fund managers according to a strategic asset allocation. Even if this is too complicated the framework allows investors to better understand past fund manager returns so as to better choose an asset allocation or cash benchmark. For managers that have significant exposure to asset classes that tend to outperform cash or inflation due to the inherent risk premia, the absolute return benchmark should be amended as such. If anything the results reveal that even hedge fund strategies like market neutral funds can be prone to some beta exposure to certain asset classes despite the perceived market neutrality.

From a different perspective hedge fund attribution has always been a difficult task given the ability for hedge fund managers to invest to varying degrees of leverage in different asset classes. This made commentary, attribution and assessment of hedge fund returns difficult to do. This framework allows investors to understand fund manager returns in the due diligence process but also as part of the ongoing assessment of fund manager returns. This allows for better understanding between fund manager and investor and can be used to understand returns in different market environments as outlined in the results section.

AREAS OF POTENTIAL FUTURE RESEARCH

HETEROGENEOUS HEDGE FUND BENCHMARKS

An important aspect of future research lies in creating heterogeneous independent variables to cater for any hedge fund or strategy. This paper focussed on a broad approach to capturing beta across asset classes and regions. This led to lack-lustre goodness of fit for strategies like commodity and even-driven hedge funds. Selecting different variables relating to different hedge fund types will allow for a focussed regression analysis and theoretically better results across the regressions and for the subsequent benchmarking of returns. It is however important to understand that the underlying asset class data may simply be unavailable.

DRIFTING WEIGHT CLONE BENCHMARKS

The method of creating the clone/benchmark portfolios and the subsequent rebalancing of those portfolios could form an interesting research effort. The clone portfolio created had a fixed weight based on a specific test period which will not work for asset allocators that need constant, updated feedback on hedge fund returns. There are various ways that the clone portfolios could be benchmarked and windows created to provide updated asset allocation information for benchmarking or narrative purposes.

THE NEED FOR RESEARCH GIVEN CHANGES TO SA HEDGE FUND REGULATIONS

From a South African perspective, the environment for hedge fund investment is changing and the research effort within this investment class should also. New regulation allows for the creation of a Retail Investor Hedge Fund (RIHF) and a Qualified Investor Hedge Fund (QIHF). Both classes have new reporting requirements with the Financial Sector Conduct Authority (FSCA) in South Africa which starts to lift the opaque nature of hedge funds. RIHFs have unique risk limits that need to be adhered to while QIHFs can exist as hedge funds did in the past though need to be registered with the conduct authority. A new, structured environment for hedge fund investment, in relation to RIHFs, is a promising new area for this research to assist in benchmarking. Given clearly stated objectives, risk limits, and asset class exposure provides the information and structure that is required to use this framework to better benchmark hedge fund returns.

From a data perspective there is still a relative lack of diversity available across hedge fund strategies and managers. This relatively small sample pool is getting larger, as evidenced by the dataset used in this paper, which makes ongoing research in this and other hedge fund topics crucial. More hedge funds and hedge fund data will provide a larger sample set thus making for more statistically significant hedge fund research.

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