



# SKILL OR LUCK: A BOOTSTRAPPING APPROACH TO ANALYSING SOUTH AFRICAN EQUITY UNIT TRUST RETURNS

By

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## Declaration

I, Luigi Marinus, do hereby declare that the work presented in this thesis, is my own, except where acknowledged and that this thesis or any part of it, has not been previously submitted for the award of a degree at any university.

Signed 

Signed by candidate
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 Date..... 29 June 2022.....

Luigi Marinus

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## **Abstract**

The focus of the study is to add to the available literature on the ability of unit trust fund managers to consistently display skill in their investment performance, and to distinguish between skill and luck. The study focussed on South African domestic equity funds and divided these between funds that have an allowance for an offshore allocation and those that are domestic only. Domestic equity funds were specifically selected as sample because they can be analysed in terms of the multi-factor equity pricing models kept up to date by Legae Peresec. These funds were further divided between those that allowed global exposure and those that did not, to test whether this had a notable effect on the performance of the two subsamples. In the South African domestic equity ASISA category (ASISA, 2021), funds have an allowance for a maximum of 30% in offshore holdings, but most funds (roughly two-thirds in this study) choose to not allow offshore holdings in their mandates. The initial sample of 326 funds reduced to 179 funds after the exclusion of tracker funds, funds of funds, multi-managed funds, and funds with either less than 36 months of performance or where required data was missing. The study uses performance data for the period March 2006 to May 2020 for all qualifying funds regardless of whether they were active at the end of the period or not, and therefore caters for survivorship bias.

Two methods are used to assess expected performance versus actual performance. The first was a regression analysis that tests fund performance against three multi-factor asset pricing models, namely the Fama and French 3-Factor Model, the Carhart 4-Factor Model, and the Fama and French 5-Factor Model. The second is a bootstrap resampling analysis that indicates whether fund performance is better than a randomised (luck-equivalent) distribution of returns, thereby implying manager skill. A regression was run per fund based on the Carhart 4-factor model with the error terms being resampled. A distribution per fund was then modelled by regression by replacing these error terms 1,000 times. A further regression was run independent of time to obtain the alphas for the comparison to the actual fund alphas. Any specific

funds with alphas greater than the distribution performed better than the model suggests at certain percentile levels, which would imply skill was required to attain those performance levels.

The first part of the study shows that certain funds outperform the multi-factor model performance over the measurement period, although in all models the average alpha is less than zero. In the second part of the study the bootstrap resampling produces a luck distribution that is compared to the actual distributions. There are no funds where the alpha exceeds the corresponding luck-based percentile level, which could imply that fund manager skill was not present over the measurement period. There are several actual fund alphas that fall within the luck distribution range of alphas, where skill was inconclusive. Funds that have a global allocation tend to perform better than local only funds before fees are taken into account.

While this study may not be the final word on whether investment skill is observable in the South African market it gives some insight into the likelihood of skill being present over a certain defined investment period. As passive funds have attracted more assets, the question of whether active investment managers are justified in earning higher fees is becoming increasingly important. The results of this study indicate that this may indeed not in general be the case.

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## Chapter 1 - Introduction

The unit trust industry has grown significantly globally, especially post the Second World War, with fund managers making investment decisions on vast amounts of investments for many clients. South Africa is no exception to this. There are currently more than 1,700 retail unit trust available for investment in the South African market. A unit trust is a collective investment product where investors funds are pooled and invested by a professional investment manager. The pooling of asset provides economies of scale and allows investors to invest relatively small amounts in a diversified product. The first open-ended unit trust, as used today, was launched in the US in 1924<sup>1</sup>. By 2020 the total assets under management by mutual funds in the US has grown to \$23.9 trillion<sup>2</sup>. Although South Africa is a smaller market than the US, there has been significant growth in the South African unit trust industry as well. The first unit trust was launched in South Africa in 1965<sup>3</sup> and by mid-2021 the unit trust assets under management had grown to nearly R3 trillion<sup>4</sup>.

Before the idea of mutual funds or unit trusts was born, stockbrokers guided investors on how to buy shares on an exchange. Investors would have close relationships with their brokers but would ultimately decide which stocks they wanted in their personal portfolios. For the most part the brokers were administrators who facilitated the buying and selling of shares on behalf of their clients. Brokers would of course be closer to the market and have ready access to more company information than their clients, even if the information was publicly available. This was translated into stock ideas for clients and brokers, with more successful ideas gaining more clients as word of the good advice spread.

By the time the unit trust industry took shape and the pooling of investments managed by a professional investor was proposed, the stockbroker model as the proposer of

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<sup>1</sup> [www.investopedia.com](http://www.investopedia.com)

<sup>2</sup> [www.statista.com](http://www.statista.com)

<sup>3</sup> [www.investonline.co.za](http://www.investonline.co.za)

<sup>4</sup> [www.asisa.org.za](http://www.asisa.org.za)

stock ideas was well established. It meant that not only was there economies of scale by pooling assets, but a professional with an understanding of the market would be responsible for investment decisions. The question investors then needed to ask was not which shares to select, but which professional investor to select. The simple decision could be based on the success (or not) of previous investments the professional had made, but how could an investor be confident that the professional would continue to be successful? This question still gets asked today: how does one know if a fund manager has skill, or was just lucky when outperforming the market?

The importance of this question is relevant for many investors, from first time investors with small monthly debit orders, to mature investors with sizable retirement funds, to asset aggregators doing manager selection for various products. If skill could be shown, then it could be repeated, and consistent performance could be expected. This question is also gaining prominence as investors are becoming more sensitive to fees and there is an increase in passive investing. Passive investing in its primary form is when a fund manager replicates an index in the stock selection and delivers a return that matches that of the chosen index. No fundamental analysis on companies is undertaken, and therefore asset management costs and the feedthrough to fees are reduced. Relative to the index that is being replicated, the risk the investor faces is implementation risk in the way that the fund manager replicates the index. Passive investing has evolved from simple market weighted products to single-factor or multi-factor models. A factor is a quantifiable attribute of a stock, that could explain how a stock return is achieved. For these products a single factor like value<sup>5</sup> or momentum<sup>6</sup>, or a combination of factors, are used to produce a new index. The index weights companies based on the dependence of each factor and fund managers replicate this index in their stock selection. A methodology of how to classify companies based on the various factors selected needs to be decided by the fund manager which may be

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<sup>5</sup> Value stocks are those that are trading below their calculated intrinsic value. Value investors believe that these stock prices will increase towards their intrinsic values over time.

<sup>6</sup> Momentum stocks are those that have increased in value over recent trading sessions. Momentum investors believe that these stock prices will continue on their price trajectory.

an industry accepted method or a proprietary one. Therefore, in setting up the rules of the index analysis is required, but once accepted a passive strategy of replicating the new index is implemented. The investor therefore faces model and implementation risk, but these products remain relatively cheap as the bulk of analysis is done prior to the inception of the fund and managed passively against the new index. When compared to traditional active management both passive and factor investing are offered at lower fees, and market weighted passive investing has no market risk. Relative to the industry accepted benchmark, factor investing does have market risk as the model will differ from the market weighted holdings. The advantage of accepting market risk is the possibility of outperforming an index by good stock selection, but poor stock selection will result in underperformance. Fees are a hurdle to performance and the higher the fees, the better the performance required to outperform the benchmark.

On this basis the thesis is topical to the investment industry as active managers are being asked to show their value add to justify their higher fees, when lower cost products are available that have proven to be competitive. This study asks the question of whether South African equity general fund managers have the skill to deliver consistent outperformance, both before and after the consideration of active investment costs. The concept of skill is based on previous studies in different countries and replicated for the South African market. South African literature is not as rich on investment skill as more developed economies, so this concept of skill is a new way of looking at the question in this market.

This study is divided into two parts. The first part uses a regression analysis approach to investigate whether there are actively managed South African equity funds that, over the period March 2006 to May 2020, on a risk-adjusted basis outperformed three well-known multi-factor models, namely the Fama and French 3-Factor Model, the Carhart 4-Factor Model and the Fama and French 5-Factor Model and, if so, what proportion of funds managed to do so. The second part uses bootstrapping

resampling and regression analysis to build a luck distribution of expected alphas (*i.e.*, excess returns above the benchmark). This alpha distribution indicates the expected pattern of randomly generated alphas – in other words, the expected “luck” distribution of alpha values (both positive and negative) generated by mutual fund performance.

The first part of the analysis is a simple standard linear regression which is required to test whether there are funds that outperform the multi-factor models (*i.e.*, that outperform on a risk-adjusted basis). The question of whether this outperformance is as a result of skill or luck leads to the second part of the analysis. The resampling component of the second part of the study is resampling the error terms, with the idea that these can be randomly distributed across any funds. Resampling is therefore done with replacement of the residuals. The bootstrapping component of the second part is running the regression 1,000 times per fund to obtain a new distribution of alphas per percentile which serves as the luck distribution. The alpha of the top fund, the 99<sup>th</sup> percentile fund, the 95<sup>th</sup> percentile fund and the 90<sup>th</sup> percentile fund is compared to the luck distribution. If there are funds with alphas that exceed the range of the luck distribution alphas, then skill is potentially present, but if alphas are below the range, then the actual performance is below that expected on the basis of luck alone. There may also be funds that fall within the range where distinguishing between skill and luck is inconclusive.

A key challenge with this study is the size of the sample available which, whilst acceptable for statistical analysis, is small compared to previous similar studies conducted in the US in particular. Also, over the time period of the performance data, momentum and growth strategies notably outperformed value strategies, highlighting the impact an investment style can have on performance when market conditions have not been conducive to that style performing well.

This study is novel and relevant from both an academic and market perspective as it may help improve the understanding of the South African equity market in an area of

relevance, especially as passive funds continue to grow in prominence in the investment industry. Skill is generally a subjective attribute, but the study quantifies it in a way that is repeatable and comparable. This comparability is an important aspect of the study as it allows for assessments of actual results against expected results. There is, however, a time dependent component that does influence the overall result and needs to be considered within the context of the time period.

The remainder of this thesis is structured as follows. Chapter 2 consists of a literature review that examines the evolution of the concept of skill versus luck within the equity investing context, starting with the Efficient Market Hypothesis, passive investing and multi-factor investing. The academic literature on whether fund managers can outperform the market is then analysed, followed by a look at literature on what investment consistency means. The final section of the literature review looks at relevant research in the South African context. This is followed by Chapter 3, which discusses the sample, data and descriptive statistics used, which is applicable to both parts of the study. Chapter 4 explains the methodology to run the regressions for the 3, 4 and 5 factor models, and summarises and interprets the results. Chapter 5 is the main focus of the study, as it explains the methodology for the bootstrap analysis and determines whether, based on this analysis, South African general equity funds managers have shown skill in delivering performance over the period. Chapter 6 concludes by summarising the outcomes, highlighting some of the shortcomings of the study, and suggesting future areas of research.

## **Chapter 2 - Literature review**

This chapter starts with a discussion of the Efficient Market Hypothesis (EMH), which theorises that investment outperformance is not possible due to perfect information. It then moves to an explanation of passive index and active investing by contrasting evidence from empirical research on the subject. A more recent expansion of passive investing has been multi-factor models that attempts to explain how certain factors make up the total return of a portfolio. Thus, detail is provided on the most widely used models and why these factors are accepted as the drivers of returns. Next, the ability of fund managers to outperform their benchmarks over time is investigated. There is a wide body of contradictory research in this regard that is considered. This leads to the question of consistency, and whether those managers that outperform the market provide evidence of consistency, how this is measured, and how skill is distinguished from luck. As this study pertains to the South African equity market, an investigation into the relevant South African mutual fund/equity literature is included to highlight the academic evidence in this regard, and to highlight idiosyncratic characteristics of the South African listed equity market.

### **2.1 The Efficient Market Hypothesis (EMH)**

The Efficient Market Hypothesis suggests that it is not possible for investment fund managers to outperform the market, as an efficient market very quickly incorporates new value-relevant information into share prices. This original concept of Bachelier (1900), was formalised into the Efficient Market Hypothesis by Fama (1965, 1970). Thus, (Fama, 1965) argues that share prices follow a random walk (*i.e.* are unpredictable), implying that the analysis of past price movement is not helpful in trying to predict future price movements. This implies that any possible skill a fund manager develops through past experience is not of any use in the present, as price movements are random. If such skill of experience is not repeatable, then any evidence of manager outperformance of the market must be due to luck. At around the same time, Samuelson (1965) proposed an alternative reasoning for the Efficient Market

Hypothesis. Instead of the random walk model suggested by Fama, Samuelson used a different stochastic process, called a martingale, which he applied to future prices on the commodities market. A martingale uses conditional probability to show that the expected value of the next variable in a sequence is equal to the current value (Doob, 1971). Samuelson used a no-arbitrage argument together with the martingale theory to show that the current stock price is the best estimator of future prices, and importantly, independent of the pattern of past prices. This therefore implies that markets are efficient, and that additional analysis of stock price history does not lead to a better estimation of future stock prices. Although both theories come to the same conclusion, Fama's random walk model is better known due to Fama's use of empirical evidence, as opposed to Samuelson's more theoretical argument. Further, Fama primarily used his theory to explain the implications on markets, while Samuelson primarily used his theory to show how it could benefit government policy making (Delcey, 2019).

Fama (1970) used both theoretical and empirical evidence to show that the Efficient Market Hypothesis does hold, implying that portfolio managers are unable to add value as any trading profits would be eliminated by costs. Fama further identified three forms of market efficiency. The first of these is weak form efficiency. Here the assumption is that if only historical prices were used for stock analysis the future stock price would follow a random walk, meaning that stock pickers using only historic share process and volumes to predict future prices will not outperform the market average. However, some subsequent studies that tested the weak form of the Efficient Market Hypothesis in different regions of the world do not necessarily agree with Fama's original study. For example, Nisar and Hanif (2012) investigated the four largest stock markets in South Asia (India, Pakistan, Bangladesh and Sri Lanka), and found empirical evidence that the stock prices in these markets do not follow a random walk in the weak form, thus affording an opportunity to benefit from technical analysis. This is further demonstrated by a wider global study by Mishra (2011) that considered stock prices in both selected emerging market countries (India, China, Brazil, South Korea

and Russia) and selected developed market countries (Germany, USA and the UK), which similarly found an opportunity to deliver outsized trading profits in what appeared to be weak-form inefficient markets. The second form of market efficiency postulated and tested by Fama was the semi-strong form. Here stock price information as well as any relevant public information is assumed to be quickly and efficiently incorporated into stock prices. Thus, this additional publicly available information does not allow for outperformance of the market as stock prices would still follow a random walk. More recent studies have at times supported, but also contradicted, these findings. Mackey and Bacon (2017), for example, showed empirically that depending on the type of public signalling the semi-strong form may or may not hold. The study used 40 companies that issued new stock and 40 companies that repurchased by comparing price action prior to and after the stock announcement. Specifically, in this analysis the issuance of new stock conformed to the semi-strong efficient market form while the repurchase of stock did not. Thathaiah and Dsouza (2013) using 160 stocks on the Indian Stock Market, found that the semi-strong form did not hold for this bourse. The conclusion suggested that this was most likely due to the speed at which information was disseminated in the Indian market, which may raise a question about the efficacy of the Efficient Market Hypothesis in emerging versus developed markets. The third form Fama identified and analysed was the strong form efficient market. This form means that even if historical prices, publicly available information and privately held information is used, outperformance of the market is still not be possible as future stock prices would still follow a random walk. Fama's premise with regards to this form of market efficiency was that when non-public information became relevant the market instantly adjusts the stock price so that no benefit from the non-public information could materialise. A critique of the strong form hypothesis is the illegality of insider trading, which has been shown by Finnerty (1976) to have a positive effect on the ability of a stock picker to outperform the market. It follows that most academic studies test for the weak and semi-strong forms of the Efficient Market Hypothesis, as empirical testing for these forms is more practical.

It is important to note that the study by Fama (1970) and other proponents of the Efficient Market Hypothesis make implied assumptions about the depth of available information in the market by considering all information, at the relevant form, to be available and the dissemination of this information as it becomes available to be instantaneous at best throughout the market, or at worst simultaneously available to the market. The implications of these assumptions mean that there is little consensus in academia on whether markets are efficient or not (Sewell, 2012). In his study of the 2008 to 2009 financial crisis Malkiel (2013), who is a well-known proponent of the Efficient Market Hypothesis, argues that it is more useful to think of the market as being reasonably efficient, which is enough to accept the basis for the Efficient Market Hypothesis. On this basis, he further argues that active fund managers do not perform better than an index, even in the stretched financial crisis situation.

## **2.2 Passive Investing**

A practical implication of the Efficient Market Hypothesis has been the rise of passive investing as opposed to active investing. Passive investing is when the investor holds all the stock in the same proportion as an index the investor is replicating (Sharpe, 1991). This is typically a broad-based market index and therefore passive investing is also known as index investing. The link between the Efficient Market Hypothesis and passive investing is the idea that if markets are efficient active stock pickers will not be able to outperform the market and index investing will therefore outperform over the long term due to the lower fees associated with passive asset management. There is a vast amount of theoretical and empirical studies that have tested this assertion.

The main initial proponents of passive investing have unsurprisingly been promoters of the Efficient Market Hypothesis like Fama and Samuelson (Delcey, 2019). John Bogle, who founded the Vanguard Group in 1974, is regarded as the father of index investing (Wild, 2009) as he was the first to offer index funds to retail investors, built Vanguard primarily through passive investing into one of the largest asset management companies in the world, and spent his career writing about and advocating for low-

cost passive investing. Bogle was not the first to argue that over the long-term investing is a zero-sum game, but he helped significantly in making the idea more widely understood and accepted (Bogle, 2009). His point was that on average all trades resulted in some winners and some losers, which would equate to the average market return. Of course, certain stock pickers may be better at certain times, but the ability to be consistently better than average is unlikely. The higher fee these active managers charged meant that the average return over time will be lower than the index strategy, given that passive investment strategies typically charge much lower fees. This argument often forms the basis for showing the merits of passive over active investing in different geographies, sectors and even asset classes (Sharpe, 2002).

Although passive mutual funds were the initial form of index investing, a newer investment vehicle, namely exchange traded funds (ETF), has become an alternative option to index investing. An ETF is an investment vehicle that tracks an index, but trades on an exchange (Gastineau, 2001). An ETF trades like a stock and therefore has live pricing and can be traded at any time the exchange is open. There has been an increase in both passive mutual fund investing and ETF investing (Garleanu & Pedersen, 2020), particularly in the US, but in other countries as well. In the US, mutual fund investing started post WWII, but only breached 20% of total equity investments in the late 1980's. Prior to that direct stock holding was the majority investment choice. Passive mutual fund investing gained some traction in early 1990's and ETFs in the late 1990's. By 2017 passive mutual fund plus ETF investing made up 20% of the total equity investments, while active mutual funds and a small amount of hedge fund investing making up 30%. The remaining 50% was in direct equity investments. This means it took more than 40 years to active mutual funds to make up 20% of equity investments and only about 20 years for passive investing to reach the same level. Also, by 2017 passive equity investing had grown to a 2:3 ratio to active equity mutual fund investing. A recent study by Anadu et al (2020) showed that by March 2020 passive investments, including both mutual funds and ETFs, made up 48% of the assets under management

in US equity funds (this excludes direct stock holdings). In addition, the study showed that total passive investments, *i.e.* for any asset class, totalled about \$8 trillion as a result of \$5.2 trillion of inflows into passive investments from January 1995 to March 2020. Over the same period, active funds received \$1.8 trillion of investments.

Somewhat paradoxically though, there is evidence (Garleanu & Pedersen, 2020) to suggest that more passive strategies in a market reduces the efficiency of that market, as active investors more readily react to new public information, therefore improving the efficiency of markets. The argument is made that active investors help with the efficiency of markets by ensuring that any public information is swiftly acted on to ensure that share prices correctly react to this new information. As passive investing follows an index, there is no fundamental analysis done to ensure the efficiency of markets. The proportion of holdings in an index, which is a function of the price of the underlying securities is accepted as correct and invested accordingly. Additional concerns about the implications of passive investing are the likely increase in correlation between index stocks, possibly as a result of less stock analysis, a change to the cashflow dynamics into and out of funds over volatile periods, and the link between ETF prices and underlying stock prices, specifically whether there may be an arbitrage opportunity in the secondary ETF market (Sushko & Turner, 2018). This and similar literature suggest that there is a limit to the maximum proportion of passive investments in a market before the efficiency of the market is jeopardised.

A seeming shortcoming of passive investing was the initial belief that if a factor could be identified that adds value over time, an investor could only benefit by using active asset management (Bender et al., 2013). More recently, however, indices have been developed that replicate the performance of a specific factor or factors, and passive trackers of these indices have become investable vehicles. By combining a number of these passive factor trackers, a multi-factor investment is possible without the requirement for active management or active fees.

## 2.3 Multi-factor models

The idea of the multi-factor model is not a new concept, although it started with a single factor, until more factors were added to the model. The initial factor model was the Capital Asset Pricing Model (CAPM), developed in the 1960's through the pioneering work of William Sharpe and John Lintner (Bhatnagar & Ramlogan, 2013), which built on the prior work of Harry Markowitz (Elbannan, 2014). Markowitz (1952) introduced the idea of portfolio selection, and subsequently formulated the relationship between risk, reward and diversification by showing that it is not the risk and return expectation of a stock that should be considered in isolation, but rather the effect on the risk and reward profile of the portfolio due to the addition of the stock (Markowitz, 1959). This insight is credited as the birth of modern financial economics. From this theory the CAPM, a theoretical single factor model that indicates whether a stock is fairly valued in relation to the risk associated with it relative to the market as a whole, was developed (Sharpe, 1964). The single factor under consideration is the stock's so-called Beta, which is a measure of the stock risk relative to the market risk. This is considered the stock's systematic risk, which is the risk that is inherent in the market and can therefore not be diversified away by adding other stocks to the portfolio. The higher the stock's systematic risk is, the higher its Beta is.

Of greater interest to this study are the multi-factor asset pricing models that have subsequently been developed. The first of these is the Fama-French 3-factor model. Fama and French (1993) and (1996) derived their 3-factor model by considering two additional factors that was found to explain the expected return of a security. It was noted that previous researchers found that other factors may influence stock performance, but that these were considered anomalies in relation to the CAPM. In addition to the market factor of the CAPM, it was empirically shown that two additional factors, company size (the small minus big factor) and book value per share (the high minus low factor) had a statistically significant effect on stock performance. It was thus found that small-cap companies perform better than large-cap companies over time,

and this additional factor adds more information to the model. Similarly, companies with high book to market values were found to outperform companies with low book values over time. This factor has become accepted as a measure of value, and hence a high book value to market value stock is seen as a value stock. By adding these two factors to the CAPM the Fama-French 3-Factor Model was developed as follows:

$$E(R_i) - R_f = b_i [E(R_M) - R_f] + s_i E(\text{SMB}) + h_i E(\text{HML}) \quad \text{Equation 2.1}$$

where SMB is small minus big, referring to the excess returns historically achieved by a portfolio of large cap companies vs. a portfolio of small cap companies, and HML is high minus low, referring to the excess returns historically achieved by a portfolio of high book-to-market value vs. a portfolio of low book-to-market value stocks, while  $R_M$  is the market return and  $R_f$  is the risk free rate. This is then used in a time-series regression with  $b_i$ ,  $s_i$ , and  $h_i$  as the slopes,  $\alpha_i$  as the intercept and  $\epsilon_i$  as in the error term in the regression model, as follows:

$$R_i - R_f = \alpha_i + b_i (R_M - R_f) + s_i \text{SMB} + h_i \text{HML} + \epsilon_i \quad \text{Equation 2.2}$$

This regression was used to run a number of tests with roughly 30 years of monthly data, and it was concluded that the 3-Factor Model is a good description of average returns, which explains some of the anomalies from the CAPM. However, Fama and French (1996) also conceded that while the 3-Factor Model is an improvement on the CAPM, it is still cannot explain all returns for stocks and portfolios, especially in the short term.

Carhart (1997) subsequently went a step further and introduced a 4-factor model, which became known as the Carhart 4-Factor Model. One of the shortcomings of the Fama and French 3-Factor Model is that it does not explain short-term performance well. Carhart attempted to address this by adding a fourth factor (known as the momentum factor) to try to explain observed short-term performance trends. This involved testing the returns of stocks (or portfolios) that had the highest returns over the past twelve months, compared to ones with the lowest return over the same

period, and the finding that the former typically outperforms the latter. The Carhart 4-Factor Model is specified as follows:

$$R_i - R_f = \alpha_i + b_i (R_M - R_f) + s_i \text{SMB} + h_i \text{HML} + p_i \text{PR1YR} + \epsilon_i \quad \text{Equation 2.3}$$

All variables are as previously defined, and PR1YR referring to the excess returns historically achieved by a portfolio of the highest 12-month return momentum vs. a portfolio of the lowest 12-month return momentum shares, and  $p_i$  as its slope.

Carhart (1997) showed that the 4-factor model greatly reduces the average pricing error compared to the CAPM and 3-factor models, especially the effect in the 3-factor model of strongly negative model errors for the previous year's poor performers, and strongly positive model errors for the previous year's good performers. Thus, according to this study, mean absolute errors reduced from 0.35% for the CAPM, to 0.31% for the 3-factor model, to 0.14% for the 4-factor model. The fourth factor further eliminated pricing error patterns. Carhart also reported that, for his sample period, buying funds that performed well over the prior year and selling those that did not, would have resulted in an average outperformance of 8%, of which more than half could be explained by market value and momentum. Of interest though was that momentum added very little explanatory value after one year, as portfolio performance moved closer to the average over time. Carhart (1997) also reported that these results were consistent with an efficient market, as only the top decile of performers outperform, but generally by only as much as their investment costs. The average fund underperforms by their investment costs and the lowest decile funds tend to outperform by about twice their investment costs.

Subsequent studies have shown a similar improvement from CAPM to the Fama and French 3-Factor Model, and then to the Carhart 4-Factor Model. For example, Bello (2008) does a statistical analysis that compares the three models. Somewhat surprisingly he found that each model had a  $R^2$  of 0.71, which means each model explained 71% of the equity returns. The quality of the prediction, however, varied noticeably as the number of factors used to define the models increased. To test the

predictive power three statistical measures were used, namely Mallor's  $C_p$ , which measures the total prediction error by taking variance and bias into effect, PRESS, which is the prediction sum of squares and  $S^2$ , which is the residual mean square. Using 20 years of monthly fund returns from April 1986 to March 2006 for various US mutual funds, the test statistics showed an improvement for each of the predictors as the number of factors increased.

Fama and French (2016) subsequently tested a 5-factor regression, which became known as the Fama and French 5-Factor Model. This was an extension of the Fama and French 3-Factor Model by the addition of profitability and investment factors but does not include Carhart's momentum factor. The profitability factor is referred to as the Robust Minus Weak (RMW) factor, defined as the historical return difference between the most profitable companies and the least profitable ones, while the investment factor is referred to as Conservative Minus Aggressive (CMA) factor, meaning the historical difference in returns between companies that invest their capital most conservatively compared to those who invest capital most aggressively. This leads to the 5-factor regression model specified as follows:

$$R_i - R_f = \alpha_i + b_i (R_M - R_f) + s_i \text{SMB} + h_i \text{HML} + r_i \text{RMW} + c_i \text{CMA} + \varepsilon_i \quad \text{Equation 2.4}$$

The first three factors are defined as in the 3-factor model, and the RMW and CMA are the profitability and investment factors with  $r_i$  and  $c_i$  being the respective slopes.

Fama and French's (2016) empirical testing of the 5-factor model indicated that positive exposures to the profitability and investment factors (*i.e.*, profitable and conservative companies) are associated with a low beta for the market and low volatility of returns, whilst negative exposures to the profitability and investment factors (*i.e.* low profitability and aggressive companies) are associated with a high market beta and high volatility of returns. It is also apparent that the 5-factor model reduces the anomalies that were unexplained in the 3-factor model. Further, the authors also tested the effect of adding a momentum factor to the 5-factor model but reported that this factor had very little effect when momentum was not a strong

characteristic of the underlying securities and that even when momentum was present the model performed poorly by showing large unexplained returns, especially among small stocks. Another favourable characteristic of the 5-factor model compared to the 3-factor model is that the high average returns in the 3-factor model that was linked to share repurchases disappeared as an anomaly due to the addition of the profitability and investment factors.

Because the 5-factor model is still relatively new, the literature available on it is not as vast as that for the 3-factor or 4-factor models. Despite this, several studies have tested the effectiveness of the 5-factor model in regions other than the US, on which the original model was based. Thus, for example, Chiah, Chai and Zhong (2015) showed that in the Australian market the 5-factor model reduces the anomalies compared to the 3-factor model, and therefore better explains the return expectation in that market. The only shortcoming noted in the study was that the model failed to explain the time-series variation in returns. A subsequent study tested the suitability of the 5-factor model in different emerging market economies, divided into three regions, namely Eastern Europe, Latin America and Asia (Foye, 2018). The results of the tests in these regions were less conclusive. Value and profitability were found to be drivers of stock returns in Eastern Europe and Latin America, but only value was a strong indicator in Asia. This would imply that the 5-factor model is an improvement on the 3-factor model in Eastern Europe and Latin America, but not so for Asia. It also implies that the size and investment factors do not add value in any of the three regions, and that there may be an argument to be made that country specific models, that apply specific factors to specific regions or countries, may be more effective. For the South African equity market specifically, Cox and Britten (2019) assessed the effectiveness of the Fama and French 5-Factor Model and found a similar result to the emerging market study mentioned above, namely that the 5-factor model is an improvement to the 3-factor model, but that the investment factor again seems to add very little value to the model.

## 2.4 Can active fund managers consistently outperform the market?

The ability of active managers to add value by attempting to consistently outperform the market has for many years been a question of much debate. Sharpe (1991) made two points when, using simple arithmetic, he firstly showed that the average actively managed dollar will return the same as the average passively managed dollar before fees, and further that, under the assumption that active fees were higher than passive fees, that the average passively managed dollar outperforms the average actively managed dollar, after fees. While this implies the inability of active managers (on average) to outperform passively managed portfolios, Sharpe recognises the ability of a minority of active managers to outperform passive investors, even after fees, but does not comment on the consistency of these superior actively managed returns or whether skill or luck may have played a part. More recently, in the wake of the increase in flows to passive funds (Anadu et al., 2020), both passive mutual funds and ETF's, there are numerous studies<sup>7</sup> that test the ability or inability of the average fund manager to beat the market. Passive fund exposure has in fact increased from 8% of the market in 2007 to 20% in 2017 (Sushko & Turner, 2018). This equates to \$8 trillion of passively managed assets, of which the majority is equities.

There are many studies<sup>8</sup> described in the academic literature that show that the average active investor is unable to outperform a passive index investment, mainly as a result of the higher fees. This inability of stock pickers to outperform passive indices was discussed in previous sections of this chapter, namely those on the Efficient Market Hypothesis (Section 2.1), passive investing (Section 2.2) and multi-factor models (Section 2.3). One additional claim that has been made is that there is a certain level of predictability in stock performance as markets may be theoretically efficient but are not strictly efficient in practice. Thus, for example, Malkiel (2003) shows that even though there is unpredictability in stock price movements, investors are not able to

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<sup>7</sup> See, for example, Coval, Hirshleifer and Shumway (2005), Cuthbertson, Nitzsche and O'Sullivan (2008), Hoch (2015), Kremnitzer (2012), Krige and Wessels (2005), Kunene (2017)

<sup>8</sup> See, for example, Bogle (2009), Fama (1965), Fama (1970), Malkiel (2013), Samuelson (1965), Sharpe (2002)

benefit abnormally from this unpredictability and the fees that are charged by investment funds result in underperformance on average on a risk-adjusted level compared to the market.

Although a seemingly large body of literature show the ability of portfolio managers to outperform passive benchmarks consistently over time to be negligible, there are arguments made that this is in fact possible. For example, by looking at various studies on mutual fund performance between 1962 and 1991, Ippolito (1993) showed, based on empirical evidence, that certain fund managers had the skill to outperform a passive benchmark. This questioned the Efficient Market Hypothesis by arguing that certain managers appeared to spend resources to find new information, and then by acting on this information were able to outperform peers. These good performers were, however, offset by those spending resources but being unable to find or act successfully on new information. In other words, just because a money manager spent more money on sourcing information, it did not mean that better returns were achieved; certain managers performed better with the additional information, while other did not. Ippolito (1993) then questions the ability to over time identify those managers who perform poorly and deny them future market share. The idea of semi-strong market efficiency is questioned in this study, as it is suggested that by using resources, more valuable information can be attained from public information. Shen (2002) finds it possible to outperform the market based on a simple market timing strategy, by showing over the period 1970 to 2000 the spread between the E/P of the S&P500 and the 3-month Treasury bill or 10-year Treasury note was a reasonable indicator of when the S&P500 Index would deliver negative returns. Three additional market-timing strategies were tested over the period which was based on components of the above spread. By employing a simple switching strategy of remaining in the market until a level in the spread was reached, and then reinvesting when the spread level moved back, he showed that four of the five strategies outperformed the market

even after fees. The strategy using only the E/P<sup>9</sup> ratio did not deliver a greater return than the index. Although this may define a strategy that has the potential to outperform an index in the US market, it is not a practical strategy for South African equity funds, which always need to have a minimum 80% equity holding (ASISA, 2021). Ortman et al (2008) empirically find that selecting well-recognised company names as a portfolio resulted in returns that more often outperformed the market return. It is also shown that the fewer companies selected, based on a greater recognition level the greater the level of outperformance in most instances. Interestingly this study was conducted among both expert investors and lay people and while the recognised portfolio generally outperformed, the experts outperformed the lay people in their own domestic markets, but lay people outperformed the experts in the international market outside their domestic market. This study arguably shows that it could be possible to outperform a benchmark but does not directly address the question of skill versus luck in achieving this outperformance.

In another example, Baks, Busse and Green (2006) empirically demonstrate another way in which a group of fund managers have outperformed the market. By holding a concentrated portfolio of only a few shares, but at higher weights, these managers outperform their more diversified counterparts by roughly 0.3% per month. In this study, portfolio concentration is measured using four statistical methods: the Herfindahl index, a normalised Herfindahl index, the Gini coefficient and the coefficient of variation. The positive result seems to imply that these managers, who outperformed due to holding concentrated portfolios, must have greater skill to make the selections that result in better performing portfolios. However, part of the conclusion suggests that it may be the confidence of the manager, rather than the perceived skill of the manager, that results in the more concentrated portfolio and the level of outperformance. Cremers and Pareek (2016) investigate whether portfolios

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<sup>9</sup> E/P is the inverse of P/E, which is the price earnings ratio

with a high active share<sup>10</sup>, which implies holdings that are different to the passive benchmark, led to outperformance over the period 1984 to 2012. The study finds that a patient investment strategy is required, by which the authors mean that the portfolio should have a stock holding duration of more than two years. They highlight that using a patient strategy and having a high active share are both key requirements to the outperformance they identify, as neither funds with high active share but a high trading strategy, nor funds with a low active share, in their study experience any outperformance. The authors identify that the main reason for the outperformance is that the managers in their sample with a high active share generally selected stocks that were shunned by the market and were willing and able to wait for the stock prices to increase in value.

An important question regarding the Efficient Market Hypothesis is that of its validity in emerging market conditions. Thus, a comparison of the performance of active versus passive funds in emerging markets by Kremnitzer (2012), using all emerging market active portfolios available to US investors according to the S&P Net Advantage Fund Screener, revealed that emerging market stock pickers over 19 years, ending 2011, were able to deliver a large outperformance of 2.75% over three years after fees. This level of outperformance suggests that emerging markets are overall inefficient, and that additional fundamental analysis can help in outperforming a passive benchmark. It must be noted that the active manager screen used in this study is broad and that there is likely to be more nuanced market efficiency results per emerging market based on the sophistication of a specific emerging market's stock exchange.

Initial analysis, especially in developed markets, seem to suggest that outperforming a passive index is unlikely, as predicted by the Efficient Market Hypothesis. However, there are some empirical studies that show outperformance to be possible. The next part of the literature that is relevant to this study deals with whether there is evidence

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<sup>10</sup> High active share is a measure of how different a stock selection is to the reference benchmark stock selection. It is the sum of the differences between the fund stock holdings and the benchmark holdings. The larger the active share, the more different the fund holdings differ from those of the benchmark.

that any outperformance is repeatable and has a level of consistency, or whether these examples are largely idiosyncratic and dependent on either the time period under investigation, or an impractical way to go about investing in order to achieve this outperformance. One aspect that does seem apparent is that emerging markets may be less efficient than developed markets, and that the possibility of achieving outperformance against a passive benchmark may be accomplished by a more in-depth analysis of publicly available information that has not yet disseminated into the market as a whole.

## **2.5 Performance consistency**

The next area of interest to this study is whether outperformance is due to skill or luck, and whether this skill can be identified if it in fact exists. Coval, Hirshleifer and Shumway (2005) show that certain investors are able to persistently beat the US market over the period January 1990 to November 1996. This is done by showing that investors who delivered top decile performance over time, are able to invest in stocks that deliver significant outperformance in the short term. Persistence is shown by investors who outperform by 12 to 15 basis points per day in a week, are then more likely to outperform the following week. Similarly, investors who delivered bottom decile performance on average invest in stocks that deliver a negative return in the short term. The consistency of these top performers is viewed as skill. An important consideration from this study is that the authors are not trying to show that all managers have skill, but that if a more specific subsector can be evaluated then skill and consistency can be identified. The ability of managers who take concentrated bets in their mutual funds compared to managers who run more diversified portfolios are assessed by Baks, Busse and Green (2006). As previously indicated, it was found that managers with concentrated portfolios outperform managers with more diversified portfolios, and that the confidence to select the stocks in the concentrated portfolios was due to manager skill. In a further study by Berk and van Binsbergen (2015), manager skill was measured not specifically by performance, but by the actual dollar

value add by a mutual fund. The authors argue that larger funds are able to add more value, but that funds become large as investors identify the manager skill and invest in these funds. Little is implied about investors ability to notice this skill in managers, but the ability to add more value than peers is perceived as skill.

Of particular importance to this study is the work done by Kosowski, Timmerman, Wermers and White (2006). These authors, using data of 1,788 US mutual funds with at least five years of data over the period 1975 to 2002, applied a bootstrap resampling methodology and found that there were in fact statistically significant examples of fund managers that delivered persistent outperformance that could be classified as skill. The authors assert that solely due to the number of equity funds available in the US there is an expectation that a certain number of funds will by chance outperform a passive benchmark. Following from this argument, they then test whether the actual number of funds that outperform by given percentages are different to the number that is expected by their random-chance base model. However, this still does not necessarily differentiate between skill and luck as luck can also be persistent, especially in a large sample. The study uses the Carhart 4-Factor Model and a bootstrap analysis which resamples the error terms. This provides information on a per fund level and not at the average fund level, as well as a non-parametric distribution of alpha's that can be compared to the Carhart modelled alphas.

The results show that there is a larger number of funds that outperform above a specific top level than would be suggested if this performance was due to luck only. The resampling of the residual (or error term) in the bootstrapping analysis redistributes these error terms randomly among the sample without affecting the alpha of each observation. In simple terms a statistical bootstrap is resampling the residuals of a model with replacement in order to build a more robust bootstrapped distribution (Hesterberg, 2005). This is particularly useful for samples that are not normally distributed, and the bootstrapped distribution can be significantly larger than the original sample set, based on the number of bootstrapped repetitions that are

conducted. The tests are initially run for the full period and the full data set, but additional tests are run to differentiate between subperiods and subgroups. With the subgroup analysis there is clear evidence of growth-orientated fund managers outperforming more than expected, while income-orientated funds do not seem to add value. There was also less evidence of outperformance over shorter time periods. This study is important as it provides a replicable way of testing whether fund managers have been able to outperform over time and more importantly, which was quite novel at the time of publication, whether any achieved outperformance was more likely due to skill or luck.

The above study was subsequently replicated in the UK and in China. Thus, Cuthbertson, Nitzsche and O'Sullivan (2008) replicate the bootstrapping analysis in the UK market. The study caters for survivorship bias and uses data for 935 unit trust and open-ended investment companies, although 93 are eliminated before testing as they are considered index tracking and hence not relevant in a study looking to test for skill. For the bootstrapping analysis a minimum of 36 months of data was required, which left 675 funds of which 189 were no longer active. In this study both the Fama and French 3-Factor Model and the Carhart 4-Factor Model are tested to see if the empirical evidence suggests a higher level of outperformance than modelled. The results are consistent with the original study, in that, among the top performing funds, there is evidence to suggest that more than luck was involved in delivering the outperformance, implying that top performing managers performed better than what was expected by pure chance, and that they therefore had some skill. On the other end, among the worst performing funds, there is evidence to suggest that the performance is more than unlucky, and that some of these managers are unskilled. One of the more interesting outcomes of the UK study was some of the funds that outperformed more than expected included amongst the non-survivors. This was a surprise as it is usually assumed that funds are closed due to poor performance.

The above study was also replicated in the Chinese market to test whether Chinese funds can beat a Chinese passive index (Yang & Liu, 2017). A total of 773 open-ended equity funds were investigated using a bootstrap approach, and no evidence of positive alpha with any statistical significance was found. The authors speculate that possible reasons for concluding that all Chinese managers are unskilled include the inefficiency of the Chinese market due to its high proportion of individual investors, the less developed nature of the Chinese fund industry leading to high trading costs, and many experienced managers have left the industry paving the way for inexperienced portfolio managers to assume more money management responsibilities. Although this study finds that none of the fund managers in the dataset showed skill, it does not imply that none of the fund managers were able to beat their benchmark over the period of investigation. However, it is found that the persistence of outperformance was not consistent enough to deliver a statistically significant level of outperformance. This is a somewhat surprising outcome for an emerging market economy. Previous literature, such as the studies by Kosowski, et al (2006) and Cuthbertson, et al (2008), seemed to suggest that due to market inefficiencies there would be an opportunity for fundamental analysis to add value. That is not the case in this study though, and the specifics of the Chinese unit trust market does not lead to this outcome.

Bootstrapping non-normally distributed data provides a robust sample that allows for the testing of not only outperformance against a passive benchmark, but also the quality of any outperformance by assessing whether it can be attributed to luck or skill. This aspect has not yet been analysed in the South African market but can add value in a market that has a number of large asset management houses with a large proportion of total listed equity assets under management, and where survivor bias is an important consideration in unit trust analysis.

## **2.6 The South African unit trust literature**

Unit trust research in the South African market started off with tests of the ability of fund managers to consistently outperform a benchmark. Thus, Krige and Wessels (2005) investigated the ability of active managers to outperform the All Share Index and then looked at whether an optimal solution included some passive investments. In this study covering the period from January 1988 to December 2003, the authors showed that the average South African equity unit trust manager was able to outperform the passive benchmark before fees were taken into account. However, after fees the average underperformed the benchmark. In contrast, Tan (2015) analysed 10 South African Equity Funds over a 70-month period when global markets experienced a period of quantitative easing and found that only one of the funds displayed a statistically significant positive alpha. In addition, none of the funds had statistically significant positive coefficients. This led to the conclusion that South African managers had neither stock selection ability nor market timing ability, although this was over a specific period and using a very small sample. Nana (2011) analysed South African equity data between 2001 and 2010 using various regression models including the CAPM, the Fama and French 3-Factor Model and the Carhart 4-Factor Model but found inconclusive results. There were examples when active managers outperformed and when they underperformed. Any persistence that was identified was only over short periods and tended to decline over longer periods.

A number of studies analysed the performance persistence of South African managers over specific periods. For example, Knight and Firer (1989) focused on actual South African mutual fund performance over the period 1977 to 1986 and noted that there was persistence in both the top performing and the worst performing funds. They looked at both risk-adjusted and non-risk adjusted performance and found that more funds outperformed benchmarks when comparing risk-adjusted returns. The period 1985 to 1995 was looked at by Meyer (1998) on a nominal and risk-adjusted basis, with the conclusion that there was persistence in top performance, but only over a short

period. Subsequently Bradfield and Swartz (2001) investigated the period from 1995 to 2001. Here the authors focused specifically on persistence and compared South African unit trust performance to peers, as opposed to an index. They therefore used a ranking methodology and found that there was clear evidence of persistence over the period as the funds that ranked highly continued to do so and delivered better returns. In his master's thesis Hoch (2015) analysed the persistence of alpha over the period 2002 to 2014 and found that only a few funds show a consistent level of persistency when compared to either an appropriate index or the peers being investigated. The investment period where persistence is most evident also varies based on the specific fund.

In conclusion, while several South African studies investigated manager skill and the persistency thereof, none of them used a bootstrap resampling methodology to test the hypothesis that certain fund managers have skill and, more specifically, to try to distinguish between skill and luck in the achievement of outperformance. The present study therefore tests the hypothesis of outperformance for the South African domestic equity mutual fund category relative to an appropriate market cap weighted index.

## **Chapter 3 – Sample, data and descriptive statistics**

Information relevant to the sample, data and descriptive statistics used in this study is presented separately in this chapter, as these are common to both the study's two empirical elements, namely the factor regression and bootstrap analyses as presented in Chapters 4 and 5, respectively.

### **3.1 Sample**

The sample used in this study consisted of South African domestic equity funds over the period of March 2006 to May 2020. This period was selected due to issues of data availability. South African domestic equity funds were selected as the study attempts to gauge fund manager skill in selecting South African listed equities, and not their skill in asset allocation ability. According to the ASISA Standard of Fund Classification for South African Regulated Collective Investment Scheme Portfolios (ASISA, 2021) a South African domestic equity fund must hold a minimum of 80% equities, but most South African equity funds only hold a small cash allocation to provide for unit trust liquidity.

The Morningstar database used for this study maintains data for various fee classes per fund, these fee classes differing in their asset management fees depending on the nature of the investor. Thus, a unit trust fund may be offered to various types of investors at different fees. The size of investment most often determines the relative cost for the investment in the unit trust, with larger (smaller) investments attracting lower (higher) fees. Unit trusts are therefore divided into different fee classes with identical underlying investments but differing in the management fee per class. For this study, in cases where there were different asset classes, the oldest class was selected, as it provides the most data points for most funds. Returns both gross and net of fees were used in this study, where gross of fee returns provide insight into managers' stock picking skills, and net of fee returns<sup>11</sup> shows the effect of fees on the

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<sup>11</sup> The oldest fund class was used

ability of fund managers to deliver returns in excess of a buy-and-hold strategy. The database contained 326 South African equity funds over the 14-year period, albeit with various tenures. Survivorship bias was eliminated, as funds that are no longer active were included in the sample data.

However, some funds were eliminated based on specific criteria as follows. Firstly, 14 funds for which the database held no data were eliminated. Secondly, 45 funds that use a tracking methodology were removed. These include basic index tracking funds or funds that track an index based on one or more factors. As these funds do not attempt to outperform an index but rather to replicate it based on market cap or a certain factor, they do not involve the stock picking skill of a manager, which is the basic question of this study.

The third criteria applied was to eliminate all fund-of-funds and multi-managed funds. These are funds where a multi-manager portfolio manager combines various unit trust funds or different domestic equity segregated mandates into one fund. Any analysis on fund-of-funds or multi-managed funds would not test managers' skill in stock selection, but rather their ability to combine funds and make timeous changes to underlying funds to outperform a benchmark or achieve a specific goal. There were 48 of these types of funds that were thus discarded.

The final criteria used to eliminate funds was a requirement for at least 36 monthly data points, which was considered the minimum to conduct a satisfactory statistical analysis. An additional 44 funds were eliminated based on this criterion. The stepwise sample filtering process is depicted below.

Total number of funds available in database	326
Eliminated:	
No data	14
Tracker funds	45
Fund-of-Funds + Multi-managed funds	44
< 36 months data	44
Final Sample	179

The final sample of South African equity funds used for the statistical analysis was 179. This is a relatively small sample compared to the similar US, UK and Chinese studies previously conducted on this topic, due mainly to the South African unit trust market being much smaller than the same industry in the above countries. Thus, for example, the two similar studies conducted in the US by Kosowski, et al (2006) and Fama and French (2016), had samples of 1,788 funds over 60 months and 1,308 funds over 273 months, respectively, while the UK study by Cuthbertson, et al (2008) included 935 funds over 204 months and the Chinese one by Yang and Liu (2017) 773 funds over 240 months.

### **3.2 Data**

The data for this study was obtained from two sources, namely Morningstar and Legae Peresec. Morningstar is a data provider that specialises in unit trust data and that maintains South African unit trust performance information for funds that are active, as well as for funds that are no longer active. Morningstar also maintains South African index data, including for listed equities and cash. Legae Peresec maintains a database of the factors for six well-known equity asset pricing factor models, namely the Fama-French 3-factor, Carhart 4-Factor, Fama-French 5-factor, AQR 6-Factor, Legae Peresec 7-factor (Low volatility) and Legae Peresec 7-factor (Low Beta) models for the South African market from 2002 onwards. The specific data required for the various regression models described in Chapter 4 of this document included the monthly returns of the FTSE/JSE All Share index (ALSI) and the Alexander Forbes Short Term Fixed Interest Composite Index (STeFI), which is a cash return and considered as a proxy for the risk-free rate, as well the coefficients for the Fama French 3-Factor, Carhart 4-Factor and Fama and French 5-Factor models.

Morningstar maintains separate datasets for both gross and net of fee returns, and among the 179 funds in the final sample there were 32 funds that had a different number of gross and net monthly data points. Missing data points were filled in using the average difference in monthly performance between the twelve most recent

common gross and net performance values. This is because the average difference was assumed to be the monthly fee, which differentiates gross of fee performance from net of fee performance. Where a fund had more gross of fee than net of fee data points, the 12-month average difference was subtracted from the gross performance. On the other hand, where a fund had more net than gross of fee data points, the 12-month average difference was added to the net performance. This increased the total number of data points and ensured the same number of data points for both gross and net of fee performance. The difference in the number of data points per fund among the 32 funds where the number of data points was not equal, ranged from one additional data point to 122 additional data points. A fund that was active for the full period had a total of 171 monthly data points. In total 675 additional data points were estimated in this way out of a total of 18,867 data points prior to the addition. This implied a 3.58% increase in the number of data points to 19,542.

The final step in preparing the data was to apply an excess return measure. All statistical analysis was done on an excess return basis, which required subtracting a monthly risk-free rate from the monthly performance data. The risk-free rate used was the Alexander Forbes short-term fixed interest rate (STeFI) composite, which is considered the benchmark cash rate in South Africa and is therefore appropriate as a risk-free rate. The monthly STeFI composite return was sourced from Morningstar.

The South African asset pricing factor data required for this study is available on the Legae Peresec website<sup>12</sup>. The latter maintain both equal and capital weighted factors for three-factor up to seven-factor models, which are calculated relative to the FTSE/JSE All-Share Index according to the international industry standard methodology. The factors for the three, four and five factor market capitalisation weighted models were used for this study. The cap weighted models were deemed appropriate as performance was compared to the ALSI, which is a cap weighted index.

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<sup>12</sup> See [www.peresec.com](http://www.peresec.com)

The risk-free monthly performance was subtracted from the gross monthly performance, net monthly performance and market factor for the various regression analyses. The table below summarises the data used.

Table 3.1 Data summary

Data Element	Source	Description
Gross performance	Morningstar	Monthly unit trust returns <i>excluding</i> asset management fees less risk-free rate
Net performance	Morningstar	Monthly unit trust return <i>including</i> asset management fees less risk-free rate
STeFI composite	Morningstar	Monthly Alexander Forbes Short Term Fixed Interest rate performance (risk free rate)
Market factor	Legae Peresec	Monthly FTSE/JSE All Share Index performance less risk-free rate
Size factor	Legae Peresec	Monthly average outperformance of small versus big companies
Value factor	Legae Peresec	Monthly average outperformance of high versus low book to market value companies
Momentum factor	Legae Peresec	Monthly average outperformance of best performing stocks versus worst performing stocks
Profitability factor	Legae Peresec	Monthly average outperformance of most profitable versus least profitable companies
Investment factor	Legae Peresec	Monthly average outperformance of companies who invest capital most conservatively versus most aggressively

### 3.3 Descriptive Statistics

The table below summarises the data characteristics for the 171 months of the sample period.

Table 3.2 Data Descriptive Statistics

	Count	Mean	Std dev	Range	Min	5%	Median	95%	Max
<b>Gross performance</b>	19542	0.14%	4.03%	51.76%	-24.81%	-6.03%	0.35%	6.28%	26.95%
<b>Net performance</b>	19542	0.05%	4.02%	51.70%	-24.89%	-6.12%	0.26%	6.17%	26.81%
<b>STeFI composite</b>	171	0.59%	0.14%	0.60%	0.39%	0.43%	0.58%	0.90%	0.98%
<b>Market factor</b>	171	0.32%	4.39%	27.65%	-14.19%	-5.90%	0.54%	7.37%	13.46%
<b>Size factor</b>	171	0.94%	4.48%	30.15%	-18.88%	-6.20%	1.17%	7.37%	11.26%
<b>Value factor</b>	171	0.57%	5.51%	62.32%	-37.42%	-6.45%	0.96%	7.61%	24.90%
<b>Momentum factor</b>	171	1.39%	4.84%	37.63%	-13.39%	-5.82%	1.79%	8.75%	24.23%
<b>Profitability factor</b>	171	0.90%	4.23%	22.33%	-11.40%	-6.14%	1.08%	7.91%	10.93%
<b>Investment factor</b>	171	1.12%	4.42%	27.81%	-13.40%	-5.90%	1.24%	7.40%	14.41%

The average monthly fund performance cannot be compared to the market factor as not all funds were active for the full investigation period. There may have been strong market periods where fewer funds were active, thereby reducing overall average fund performance, or vice versa. Of interest is the larger differential between the minimum performance and the 5<sup>th</sup> percentile performance, compared to the maximum performance and 95<sup>th</sup> percentile performance, when comparing the fund performance to the market factor. These differences are roughly 18% and 20% for the funds and 8% and 6% for the market factor, respectively. This could imply that most funds deliver returns similar to the market factor or within a narrow range, but active management resulted in a small number of funds significantly out or underperforming at certain times. While this may not be conclusive due to the shorter tenure of some funds, the range highlights the potential differential between active fund returns and the index.

The difference between gross and net performance implies an average fee of 0.09% per month, which implies an annual management fee of roughly 1.1%. This is consistent with the author's experience of the industry. The risk-free rate (STeFI) delivered a positive return over all 171 months, with a low standard deviation and small range of 0.6% compared to the sample. Among the factor data the value factor has a notably higher standard deviation and range as well as a significantly smaller minimum than other factors. This sizable minimum could imply that funds that invest with a value philosophy may be the ones that experienced larger drawdowns. Both the value and the momentum factors have maximum values larger than the other factors, which may at times have benefitted funds following these investment philosophies. The factors may also point to which investment styles may have benefitted over the investment period as a result of the associated factors outperforming. Momentum appears to be the best performing factor over the period with a minimum similar to other factors, but a higher average and higher maximum over the period. Both the Fama-French 3-Factor and 5-Factor models do not include momentum, but the Carhart 4-Factor model does, which may have an influence on the factor model regression (Chapter 4), as well as the bootstrap analysis (Chapter 5) where the Carhart model was used.

As the sample was an unbalanced panel accounting for survivorship bias, the number of data points (months) per fund varied between 36 and 171, as most funds were launched after March 2006. The sample contained a total of 19,542 monthly returns, which averages 109 months of data per fund, or just more than nine years of data each. The table below summarises the fund coverage and fund tenures for the full sample, as well as for the subsamples of funds with global exposure and local only exposure.

Table 3.3 Sample tenure

	<b>Months of data for total number of funds</b>	<b>Months of data for funds with global exposure</b>	<b>Months of data for funds with local only exposure</b>
<b>Mean</b>	109	124	101
<b>Median</b>	103	141	94
	<b>Total number of funds</b>	<b>Number of funds with global exposure</b>	<b>Number of funds with local only exposure</b>
<b>All periods</b>	179	62	117
<b>3-5 years</b>	38	10	28
<b>5-10 years</b>	67	15	52
<b>&gt;10 years</b>	74	37	37

As an indication of relative performance each fund's returns was compared to the FTSE/JSE All Share Index over the period of data availability for that fund. Gross of fees, 57 funds outperformed the index, with 122 underperforming, implying that 31.8% of funds did better than the index over their respective periods. Of the 46 funds with a full history over the study period, 16 funds (34.8% of the total) outperformed the index, which is slightly higher than the full sample. In the sample there were 41 funds that were inactive as of May 2020, and only six of these funds outperformed the index.

Net of fees a total of 32 funds outperformed the index, which meant that 17.9% of funds outperformed, with seven funds (or 15.2% of funds) with a full history outperforming the index. There was only one fund that was no longer active that outperformed the index. It may appear strange that a fund that outperformed its benchmark since inception was closed. Closer analysis revealed that this fund experienced strong outperformance early on but underperformed the benchmark by more than 18% per annum over the last three years at the time of closing. In addition,

the fund either had sizable outflows or did not appear to gain traction with investors as it had assets under management of only R23m a month prior to closing.

Of interest in the domestic equity space in South Africa is the extent to which the mandate of each mutual fund allows it to hold offshore listed equities in addition to domestic ones. The ASISA South Africa equity general category allows for a domestic fund to have a maximum allocation of 30% to offshore listed equities. Some funds choose to use some or all of this allowance, while others only invest in South African listed equities. The rationale is that either the asset allocation decision is given to the portfolio manager to attempt to maximise the return with a larger universe or the investor retains the asset allocation decision by independently investing in a dedicated global (offshore) offering if required. The relative performance of these subsets of funds have varied over time, based on the relative performance of global to South African equities and the relevant currency moves. The sample was divided into funds with global allocations and funds with no global allocations. A total of 62 funds had global allocations with 117 funds being domestic only (*i.e.*, had no foreign equity exposure). Gross of fees, 26 of 62 funds with global allocations outperformed the domestic only index, meaning that 41.9% of funds outperformed, while 31 of the 117 domestic only funds (26.5% of these funds) outperformed the index. When compared net of fees, 13 of the 62 funds with global allocations outperformed the All-Share Index, while 19 of the 117 domestic only funds outperformed the index (21.0% and 16.2%, respectively). At first glance it may appear that equity funds with a global allowance perform better, but they appear to have higher fees as well.

From the preliminary and superficial analysis of the data and sample fund information, it would appear that many (if not the majority) of funds do not outperform the ALSI as benchmark. This observation is explored in more depth and in a more scientifically rigorous way in Chapters 4 and 5, which respectively describes the regression and bootstrap analysis components of this study.

## **Chapter 4 – Factor Models: Methodology and Results**

This chapter describes the regression component of this study, which involved the use of the well-known Fama-French 3-Factor (Fama & French, 1993), Carhart 4-Factor (Carhart, 1997) and Fama-French 5-Factor (Fama & French, 2016) models to analyse the gross and net of fee risk-adjusted performance for the sample of 179 South African domestic equity funds.

### **4.1 Methodology**

The sample and data used to conduct the factor model regression were as shown in Table 3.1 in Chapter 3, with the relevant data consisting of gross performance, net performance, the STeFI composite as well as the market, size, value, momentum, profitability and investment factors. Two sets of regressions were run using a statistical program, with the output of interest being the alpha for each set of regressions, which indicates whether a fund outperformed or underperformed on an excess return basis. Regressions were run on the total sample set per fund, as well as separately for the domestic only portion of the sample and the portion that contained global investments. The regressions were also independently run for gross and net of fee performance to also establish the effect of fees on the number of funds outperforming on an excess return basis. The regressions were run as follows.

Firstly, three asset pricing models were identified to be used in the regression to establish risk-adjusted returns for the various funds. These models were the Fama and French 3-Factor Model (Equation 2.1), the Carhart 4-Factor Model (Equation 2.3), and the Fama and French 5-Factor Model (Equation 2.4). Availability of data and rich literature on these models, led to the decision to use these three most popular factor models.

In all three models the dependent variable is the fund performance for the month, while the independent variables were as below.

Table 4.1 Independent variables

<b>Model</b>	<b>Independent variables</b>				
3-Factor model	Market	Size	Value		
4-Factor model	Market	Size	Value	Momentum	
5-Factor model	Market	Size	Value	Profitability	Investment

The dependent variable was the monthly fund performance sourced from Morningstar for the tenure of each fund. The tenure varied based on the inception date and end date (if applicable) of each fund. Two sets of regressions were run for each fund for each model: one the dependent variable the monthly gross of fee fund return, and the other using the net monthly return. This provided the regressed alphas separately for the two datasets. The model coefficients for the independent variables were sourced from Legae Peresec as per Tables 3.1 and 4.1. These independent variables were the same for both the gross of fee and net of fee analyses.

Standard linear multiple regressions with the corresponding number of independent variables were run. The output for each of the 18 regressions, tabled below, was a distribution of alphas that is analysed in more detail in the results. An additional regression using the average of all the funds per month was considered but deemed irrelevant unless the weighted average, based on size of fund, was available and used for the average fund calculation. This information could not be readily sourced.

Table 4.2 Regressions

<b>Regression no.</b>	<b>Sample size</b>		<b>Fees</b>	<b>Factor model</b>		
1 – 3	Total	179	Gross of fee	3-factor	4-factor	5-factor
4 – 6	Total	179	Net of fee	3-factor	4-factor	5-factor
7 – 9	Local only	117	Gross of fee	3-factor	4-factor	5-factor
10 – 12	Local only	117	Net of fee	3-factor	4-factor	5-factor
13 – 15	Global included	62	Gross of fee	3-factor	4-factor	5-factor
16 – 18	Global included	62	Net of fee	3-factor	4-factor	5-factor

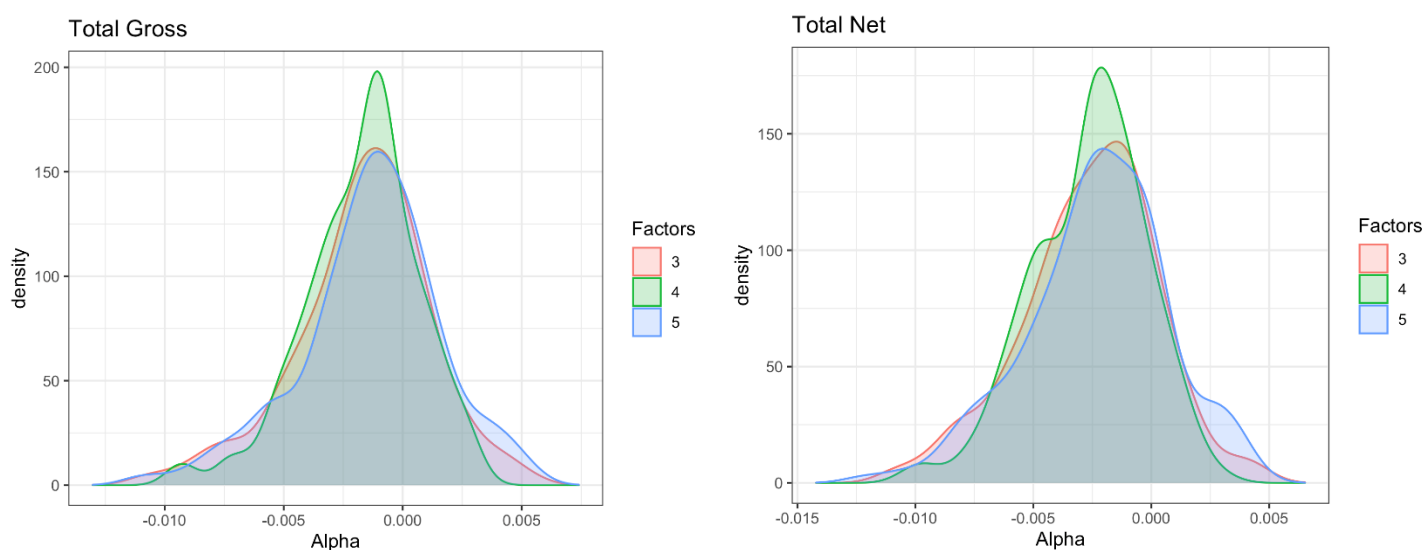
## 4.2 Results

The results are presented separately for the total sample, local only subsample (the funds that only invest in South African equities) and the global subsample (funds that may also allocate some investments to offshore equities). Both gross and net of fees comparisons are shown for each of these subsamples.

### 4.2.1 Total sample

The total sample consisted of 179 funds, with regression models run for each fund for each of the 3-, 4- and 5-factor asset pricing models, in each case both gross and net of fees.

Figure 4.1 Distribution of alphas for total sample, both gross and net of fees



The distributions for both gross and net of fee performance show a greater number of alphas lower than zero than greater than zero, implying larger levels of risk-adjusted underperformance than outperformance among the sample funds. While the 3 and 5-factor models have a similar distribution, the 4-factor model displays a greater number of alphas close to the median level. This seems to imply that the additional two factors, namely the profitability and investment factors, added little explanatory value to the 5-factor model over the 3-factor model for the sample over the period. The

momentum factor, which differentiates the 4-factor from the 3-factor model, did however make a noticeable difference to the distribution. This is consistent with the descriptive statistics that suggested the momentum factor was the most influential of the factors being tested over the sample period.

The table below provides more details on the specific output of the regression analysis by ranking the frequency of alphas over smaller ranges.

Table 4.3 Alpha count per range for total sample, both gross and net of fees

<b>Total sample - Gross of fees (179 funds)</b>			
	<b># of fund <math>\alpha</math>'s in range by model</b>		
<b>Alpha range</b>	<b>3-factor</b>	<b>4-factor</b>	<b>5-factor</b>
<(0.012)	0	0	0
(0.012) - (0.010)	2	0	2
(0.010) - (0.008)	5	3	2
(0.008) - (0.006)	5	5	10
(0.006) - (0.004)	20	21	14
(0.004) - (0.002)	39	44	35
(0.002) - 0.000	60	65	58
0.000 - 0.002	35	33	41
0.002 - 0.004	9	8	10
0.004 - 0.006	4	0	7
>0.006	0	0	0
<b>Positive alpha</b>	48	41	58
<b>% of sample</b>	26.8%	22.9%	32.4%
<b>Negative alpha</b>	131	138	121
<b>% of sample</b>	73.2%	77.1%	67.6%
<b>Average</b>	-0.00167	-0.00172	-0.00138
<b>Median</b>	-0.00138	-0.00130	-0.00118

<b>Total sample - Net of fees (179 funds)</b>			
	<b># of fund <math>\alpha</math>'s in range by model</b>		
<b>Alpha range</b>	<b>3-factor</b>	<b>4-factor</b>	<b>5-factor</b>
<(0.012)	0	0	1
(0.012) - (0.010)	2	1	1
(0.010) - (0.008)	8	3	6
(0.008) - (0.006)	12	13	13
(0.006) - (0.004)	29	36	24
(0.004) - (0.002)	47	54	50
(0.002) - 0.000	53	49	47
0.000 - 0.002	22	21	24
0.002 - 0.004	4	2	12
0.004 - 0.006	2	0	1
>0.006	0	0	0
<b>Positive alpha</b>	28	23	37
<b>% of sample</b>	15.6%	12.8%	20.7%
<b>Negative alpha</b>	151	156	142
<b>% of sample</b>	84.4%	87.2%	79.3%
<b>Average</b>	-0.00260	-0.00265	-0.00231
<b>Median</b>	-0.00236	-0.00237	-0.00208

A relatively small proportion of funds delivered a positive alpha gross of fees under all three asset pricing models used, and therefore can be said to have outperformed on an excess return basis. The impact of fees, as tested in the net of fee regressions, reduces the number of funds with a positive alpha by roughly 10% for each factor model. All average and median alphas for the three factor models, both gross and net

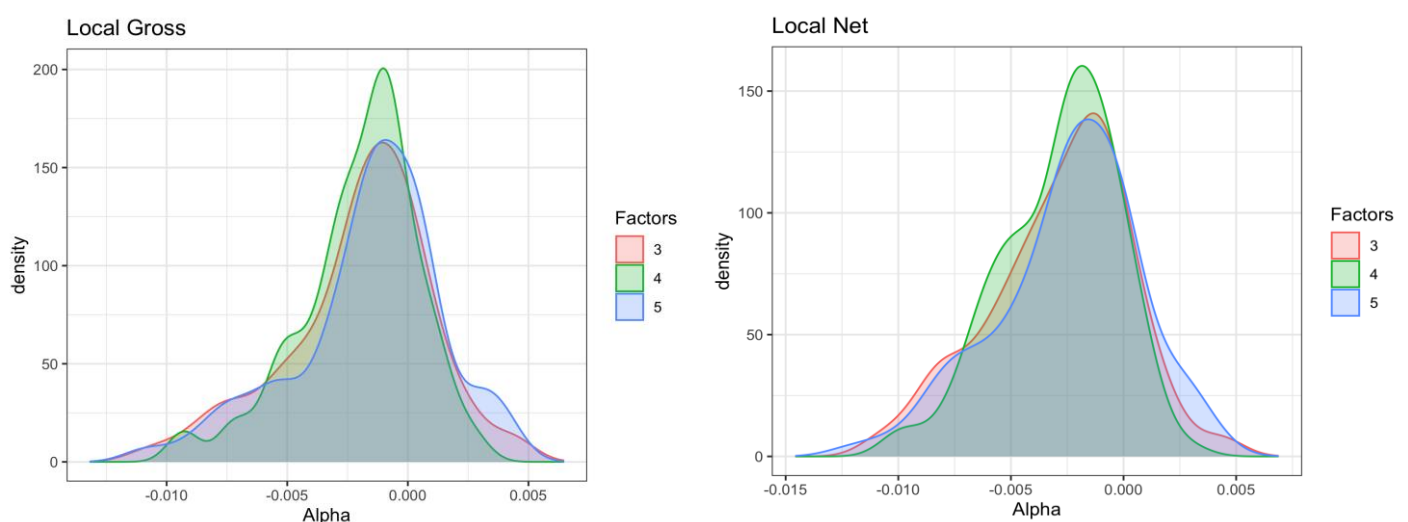
of fees, are negative, further highlighting the difficulty of funds (on average) to outperform on a risk-adjusted basis.

When comparing the three models used, the 4-factor model produced the least number of outperforming funds. This is possibly explained by the momentum factor which is only included in the 4-factor model, being the best performer over the sample period and cap-weighted indices benefitting from an improvement in momentum. As momentum improves, the underlying stocks that benefit most become larger in the index, resulting in a compounding effect as the index does not rebalance. A good example of this is Naspers on the South African stock exchange. As the Naspers share price increased, the stock became significantly larger on the exchange and at one point represented more than a quarter of the value of the exchange. Fund managers are less likely to hold momentum winners for as long, as they tend to take profits and search for new investment opportunities. The 4-factor regression also has less positive and negative outliers than the 3-factor and 5-factor regressions, which most likely indicates a better model fit as more alphas are closer to the average.

#### 4.2.2 Local only subsample

The local only subsample consisted of 117 funds that were only mandated to invest in South African equities. As before, regressions were run for each fund, based on the 3-, 4- and 5-factor models, both gross and net of fees.

Figure 4.2 Distribution of alphas for local only subsample, both gross and net of fees



The distribution profile of the local only subsample is similar to that of the total sample, probably as a result of the local only subsample being about two-thirds of the total sample. The 3-factor and 5-factor model alphas are nearly identical in distribution, while the 4-factor model alphas appear more concentrated around the average. All three models have more alphas less than zero than alphas greater than zero, implying that more funds underperformed than outperformed on an excess return basis over the sample period.

The table below provides more specific information on the alphas.

Table 4.4 Alpha count per range for local only subsample, both gross and net of fees

<b>Local only subsample - Gross of fees (117 funds)</b>				<b>Local only subsample - Net of fees (117 funds)</b>			
	<b># of fund <math>\alpha</math>'s in range by model</b>				<b># of fund <math>\alpha</math>'s in range by model</b>		
<b>Alpha range</b>	<b>3-factor</b>	<b>4-factor</b>	<b>5-factor</b>	<b>Alpha range</b>	<b>3-factor</b>	<b>4-factor</b>	<b>5-factor</b>
<(0.012)	0	0	0	<(0.012)	0	0	1
(0.012) - (0.010)	2	0	2	(0.012) - (0.010)	2	1	1
(0.010) - (0.008)	5	3	2	(0.010) - (0.008)	8	3	6
(0.008) - (0.006)	5	5	9	(0.008) - (0.006)	10	12	10
(0.006) - (0.004)	14	15	8	(0.006) - (0.004)	17	22	14
(0.004) - (0.002)	22	28	21	(0.004) - (0.002)	26	30	29
(0.002) - 0.000	42	45	37	(0.002) - 0.000	36	35	31
0.000 - 0.002	19	18	28	0.000 - 0.002	14	13	17
0.002 - 0.004	5	3	7	0.002 - 0.004	2	1	7
0.004 - 0.006	3	0	3	0.004 - 0.006	2	0	1
>0.006	0	0	0	>0.006	0	0	0
<b>Positive alpha</b>	27	21	38	<b>Positive alpha</b>	18	14	25
<b>% of sample</b>	23.1%	17.9%	32.5%	<b>% of sample</b>	15.4%	12.0%	21.4%
<b>Negative alpha</b>	90	96	79	<b>Negative alpha</b>	99	103	92
<b>% of sample</b>	76.9%	82.1%	67.5%	<b>% of sample</b>	84.6%	88.0%	78.6%
<b>Average</b>	-0.00199	-0.00201	-0.00165	<b>Average</b>	-0.00282	-0.00284	-0.00248
<b>Median</b>	-0.00151	-0.00149	-0.00126	<b>Median</b>	-0.00243	-0.00244	-0.00208

The 3-factor and 4-factor regressions produced a smaller proportion of funds that outperformed on an excess return basis, while the 5-factor regression showed a greater proportion of funds outperforming compared to the total sample. However,

the average and median alphas are lower for all factor models, gross and net of fees, in the local only subsample compared to the total sample.

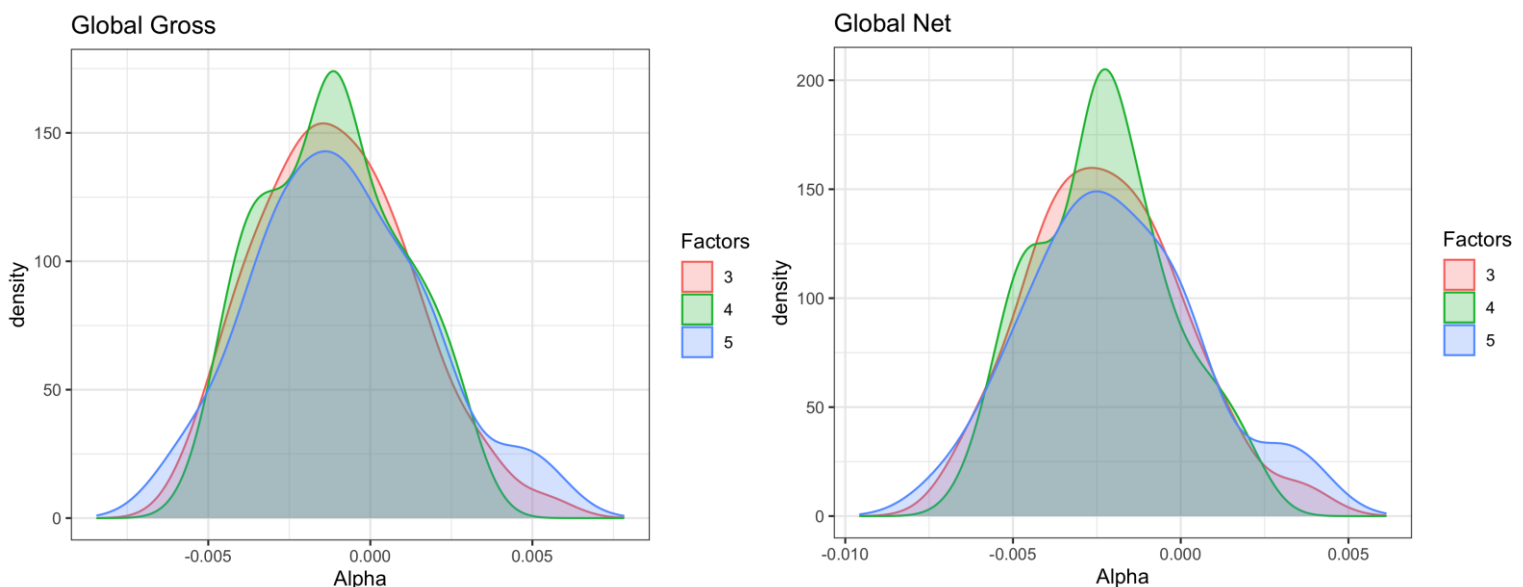
Again, the 4-factor regression deliver the smallest number of funds outperforming, gross and net of fees, and the lowest average alpha among the three models. Like the total sample, the average and median of the 4-factor alphas are similar to the 3-factor alphas, with the 3-factor median being lower in certain instances.

The 4-factor regression produced fewer outliers than the other regressions and the alphas were more closely grouped to the average.

### 4.2.3 Global subsample

The global subsample consists of 62 funds that were not limited to investing in South African equities only, but also (within limits) in international equity. As before, regressions were run for each fund based on the 3-, 4- and 5-factor asset pricing models, both gross and net of fees.

Figure 4.3 Distribution of alphas for global subsample, both gross and net of fees



The distribution profiles for the global subsample is noticeably different from the total sample and local only subsample. There is a distinct difference between the 3-factor and 5-factor alpha distributions, which differs from the total sample and local only

subsample. The 4-factor distribution again has the highest number of alphas similar to the average, but the 3-factor distribution has more alphas close to the average than the 5-factor distribution and has a noticeably smaller positive and negative tail. While there still appears to be more alphas below zero than alphas greater than zero, the proportion of negative alphas are less than both the total sample and domestic only subsample. The larger universe of stocks available globally including sectors not available in the South African equity market may be a reason for the higher alphas achieved by funds using the offshore allowance. The general depreciation of the rand against developed market currencies also had a positive effect of offshore exposures translated to rands over the period of investigation.

The table below provides more specific information on the alphas.

Table 4.5 Alpha count per range for global subsample, both gross and net of fees

<b>Global subsample - Gross of fees (62 funds)</b>			
	<b># of fund <math>\alpha</math>'s in range by model</b>		
<b>Alpha range</b>	<b>3-factor</b>	<b>4-factor</b>	<b>5-factor</b>
<(0.012)	0	0	0
(0.012) - (0.010)	0	0	0
(0.010) - (0.008)	0	0	0
(0.008) - (0.006)	0	0	1
(0.006) - (0.004)	6	6	6
(0.004) - (0.002)	17	16	14
(0.002) - 0.000	18	20	21
0.000 - 0.002	16	15	13
0.002 - 0.004	4	5	3
0.004 - 0.006	1	0	4
>0.006	0	0	0
<b>Positive alpha</b>	21	20	20
<b>% of sample</b>	33.9%	32.3%	32.3%
<b>Negative alpha</b>	41	42	42
<b>% of sample</b>	66.1%	67.7%	67.7%
<b>Average</b>	-0.00107	-0.00116	-0.00087
<b>Median</b>	-0.00129	-0.00119	-0.00093

<b>Global subsample - Net of fees (62 funds)</b>			
	<b># of fund <math>\alpha</math>'s in range by model</b>		
<b>Alpha range</b>	<b>3-factor</b>	<b>4-factor</b>	<b>5-factor</b>
<(0.012)	0	0	0
(0.012) - (0.010)	0	0	0
(0.010) - (0.008)	0	0	0
(0.008) - (0.006)	2	1	3
(0.006) - (0.004)	12	14	10
(0.004) - (0.002)	21	24	21
(0.002) - 0.000	17	14	16
0.000 - 0.002	8	8	7
0.002 - 0.004	2	1	5
0.004 - 0.006	0	0	0
>0.006	0	0	0
<b>Positive alpha</b>	10	9	12
<b>% of sample</b>	16.1%	14.5%	19.4%
<b>Negative alpha</b>	52	53	50
<b>% of sample</b>	83.9%	85.5%	80.6%
<b>Average</b>	-0.00220	-0.00229	-0.00199
<b>Median</b>	-0.00221	-0.00234	-0.00209

The proportion of funds that produced a positive alpha is similar for the 3-factor, 4-factor and 5-factor regressions, particularly in the gross of fees subsample. The 3-factor and 4-factor regressions show a larger proportion of funds outperforming compared to the total sample or local only subsample, while the proportion of funds outperforming in the 5-factor regression is largely unchanged, regardless of the sample. This may indicate that, at least over the sample period, there was an advantage to holding global underlying stocks in a domestic portfolio that is benchmarked against a domestic only cap-weighted index. This seems to be particularly true for the 3-factor and 4-factor regressions, where the larger investment universe allowed for better returns relative to these factors. For the 5-factor model there appears to be less benefit from investing globally when considering the profitability and investment factors.

There is a sizable depreciation in the proportion of funds outperforming from the gross to the net global subsample. This is likely an indication of a higher fee charged for funds where global underlying stocks are held. This may be a higher management fee, justified by the additional research requirement in analysing global stocks, or may be due to higher transactional cost in investing offshore.

### **4.3 Conclusion**

The aim with the 3-factor, 4-factor and 5-factor regressions was to ascertain if funds were able to deliver a positive alpha (*i.e.*, risk-adjust return) in terms of three best-known and most widely used equity pricing models. The results of this investigation indicated that few funds produced a positive alpha or outperformed on a risk-adjusted basis, and that having global exposure appeared to increase the possibility of a positive alpha, particularly from a gross of fee perspective. A possible explanation for this is that most South African equity managers would have identified themselves as value managers or used a valuation methodology in constructing their portfolios. Value, as table 3.2 showed was the most volatile of the factors over the investigation period and had the deepest drawdown, which would make it harder for a fund using a value

philosophy to produce higher alphas. Opposed to that momentum was the strongest factor over the period and stock indices benefit from momentum as the largest holdings in the index become larger as the price increases, without any rebalancing. A fund manager would likely be more cognisant of the risk of a single or a few large holdings in a fund and is more likely to reduce the exposure after a strong period of performance. Specific examples are the large exposures in the All Share Index to BHP Billiton and Anglo American in 2007/2008 and to Naspers more recently. Even though fewer funds outperformed, there are some funds that produce positive alpha, both gross and net of fees. What is however unclear, is whether these funds outperformed based on luck or not. This is the question that will be addressed in the next chapter.

## Chapter 5 – Bootstrapping: Methodology and Results

The focus of the bootstrapping resampling methodology is to test whether fund outperformance is due to skill or luck. As highlighted in the literature review, there is a statistical possibility that certain funds will outperform due to pure chance (*i.e.*, luck), especially if the sample is large (Kosowski et al., 2006). This part of the investigation compares the luck distribution constructed using a bootstrapping resampling method to the actual distribution found for the sample over the period covered by this study. The luck distribution predicts the proportion of funds that are expected to outperform due to randomness, and this is then compared to the actual observed performance distribution to assess to what extent any perceived outperformance differs from what could be expected from pure randomness alone. The alphas generated by the multiple regressions conducted are compared by looking at the distributions of the top performing fund, the 99<sup>th</sup> percentile fund, 95<sup>th</sup> percentile fund and the 90<sup>th</sup> percentile fund for both the luck distribution and the actual distribution. As the study is focused on identifying skill versus luck in outperformance, the top performing funds are of particular interest.

If, for example, the alpha of the top performing fund is above the range of alphas for the luck distribution, then it can be concluded that the fund manager displayed skill in delivering more alpha than random luck would suggest. Similarly, if the observed alphas of the top percent of funds fall above the top ten percent of alphas of the random bootstrapped fund distribution, then there are grounds for concluding that the top ten percent of funds displayed some degree of investment skill over and above any possible luck involved. On the other hand, if the top ten percent fund alphas fell at or below the equivalent cut-off in the random distribution, then any observed outperformance cannot be differentiated from pure chance (or luck). The same reasoning would apply to any percentile fund cut-off.

For comparative purposes the 4-factor Carhart Model is used for the regression analysis, as it was the basis of previous studies<sup>13</sup> as mentioned in the literature review. Further, the factor analysis conducted in Chapter 3 of this study suggests it to be the most difficult to outperform over the sample period, thereby making the results more stringent and lastly, the momentum factor, which over the sample period appears to have been the best performing factor, is only included in the 4-factor model, which again makes it the most relevant model to use.

The analysis is done both gross and net of fees. However, as the rationale in determining skill is outperformance compared to a relevant benchmark, gross performance is more relevant in determining skill, as it compares like for like (*i.e.*, the level of management fees charged should not affect actual investment skill). The net of fees analysis gives a perspective on the actual risk-adjusted performance experienced by the investor – in other words, it tests whether any possible skills based outperformance is sufficient to compensate for fees.

As was the case with the regressions described in Chapter 3, the comparison is performed for the total fund sample, the local-only subsample, and the global subsample.

## **5.1 Methodology**

The sample and data as described in Chapter 3 were also used to conduct the bootstrapping resampling, and the factor model regression was identical to that implemented as described in Chapter 4 for the 4-Factor Carhart model. The profitability and investment factors shown in Table 3.1 were not used, as they are only found in the Fama and French 5-Factor model (Fama & French, 2016). However, gross performance, net performance, and the STeFI composite, as well as the market, size, value and the momentum factors were used.

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<sup>13</sup> See, for example, for the US Kosowski et al. (2006), for the UK Cuthbertson, Nitzsche and O'Sullivan (2008), and for China, Yang and Liu (2017)

For the actual distribution of alphas, as in Chapter 3, a regression was run on the total sample, the local-only subsample, and the global subsample, both gross and net of fees, using the 4-factor Carhart model.

For the luck distribution the following steps were followed as per the original bootstrapping study (Kosowski et al., 2006):

### **Step 1**

The regression for each fund  $i$  was run for the actual sample, as explained above, and the residuals and coefficients of the independent variables were saved. The point of this step was to obtain the residuals, as this was later used in the resampling. As the residuals are the unexplained portion of performance it is uncertain whether these residuals are present as a result of skill or luck.

### **Step 2**

The residuals determined in Step 1 were used as a sample with replacement to calculate new returns. These new returns were obtained by randomly substituting the residuals obtained in Step 1 into the Carhart 4-Factor Model as below:

$$r_{it}^d = b_i(RM - R_f)_t + s_iSMB_t + h_iHML_t + p_iPR1YR_t + \epsilon_{it} \quad \text{Equation 5.1}$$

where

- $r^d$  is the bootstrapped return obtained by substituting the residuals
- $i$  is the fund
- $t$  is the time
- $b$  is the market factor
- $s$  is the size factor
- $h$  is the value factor
- $p$  is the momentum factor
- $R_M - R_f$  is the market less risk-free rate variable
- $SMB$  is the size variable

- HML is the value variable
- PR1YR is the momentum variable
- $\epsilon$  is the residual that is resampled as determined in Step 1

The objective of Step 2 was to determine new returns based on the sampled residuals per fund for the time (months) that the fund was active. This step is then repeated 1,000 times so that each of the 179 funds have 1,000 returns.

### Step 3

For each fund a new Carhart Model regression was run, using the randomly generated sequence of returns generated for each fund as obtained in Step 2. As funds had different tenures, the residuals were randomly assigned and hence not matched to the original time sequence. This process was repeated 1,000 times. In other words, each fund went through the bootstrap process 1,000 times based on the 4-Factor Carhart model, resulting in a distribution of 179 alphas (one per fund) for each of the 1,000 bootstraps.

$$r_i^d \sim (R_M - R_f) + \text{SMB} + \text{HML} + \text{PR1YR} \quad \text{Equation 5.2}$$

where

- d is 1 to 1,000 for the number of times the bootstrap was run
- i is the fund
- $R_M - R_f$  is the market less risk-free rate variable
- SMB is the size variable
- HML is the value variable
- PR1YR is the momentum variable

The aim of this step was therefore to use the resampled returns obtained in Step 2 and run a regression to obtain new alphas. This regression was bootstrapped 1,000 times per fund which resulted in 179 alphas per bootstrap.

#### **Step 4**

The aim in this step was to construct luck (or random) distributions of alphas based on pre-determined percentile rankings. These percentile rankings were for the 100<sup>th</sup> percentile fund (*i.e.* the top fund), the 99<sup>th</sup> percentile fund, the 95<sup>th</sup> percentile fund and the 90<sup>th</sup> percentile fund. For the top fund the highest alpha of the 179 in each of the 1,000 bootstraps was selected. This meant that there was no consistent top fund, as the highest alpha in each bootstrap may have been from different funds. The 1,000 top alphas selected was then the luck distribution of alphas for the top fund (or 100<sup>th</sup> percentile fund). This was repeated for the 99<sup>th</sup> percentile fund, the 95<sup>th</sup> percentile fund and the 90<sup>th</sup> percentile fund, which resulted in a luck distribution of alphas for each.

#### **Step 5**

The final step was the comparison between the luck distribution at these specific fund percentiles and the actual alpha based on the 4-Factor Carhart Model to determine whether more funds outperformed than the luck distribution suggested. If the alpha of the actual fund corresponding to the percentile fund was greater than the range of alphas, then skill was evident. However, if the alpha of the actual fund was below the range of alphas, then no skill was evident. If the alpha of the actual fund was within the range, then a proportional level of skill was evident based on where the alpha ranked relative to the luck distribution.

### **5.2 Results**

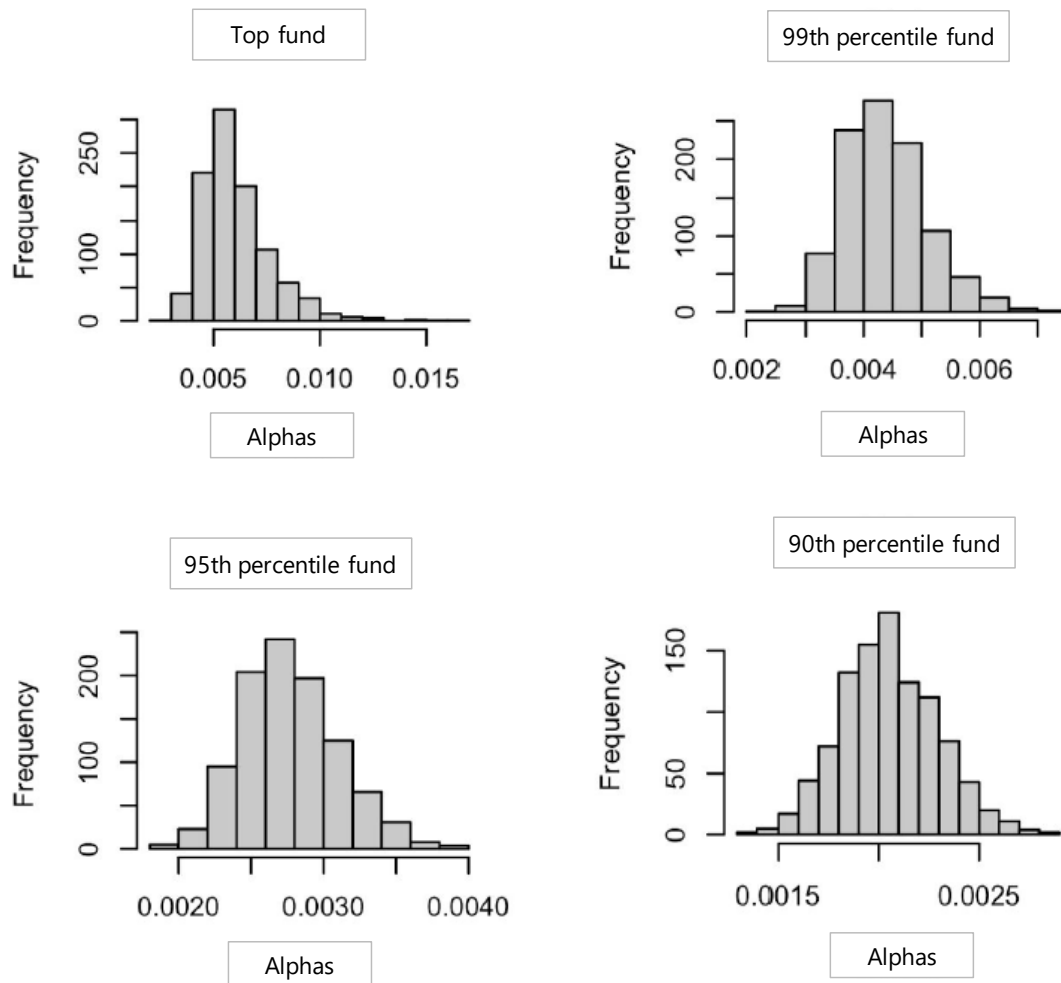
The results are again presented separately for the total sample, local only subsample and global subsample, both gross and net of fees.

#### **5.2.1 Total sample**

The gross and net of fees comparison are shown separately. The figures that follow show the gross of fees distribution of the top fund, 99<sup>th</sup> percentile fund, 95<sup>th</sup> percentile fund and the 90<sup>th</sup> percentile fund for the luck distribution.

### 5.2.1.1 Total sample – Gross of fees

Figure 5.1 Gross of fees luck distributions for total sample



As the percentile ranking reduces, the range of the distribution narrows and all distributions appear to have more alphas to the right-hand side of the distribution, which means the luck distribution has more strong performers at each percentile and makes skill more difficult to show.

Table 5.1 Alpha frequency of luck distribution versus actual gross of fees for total sample

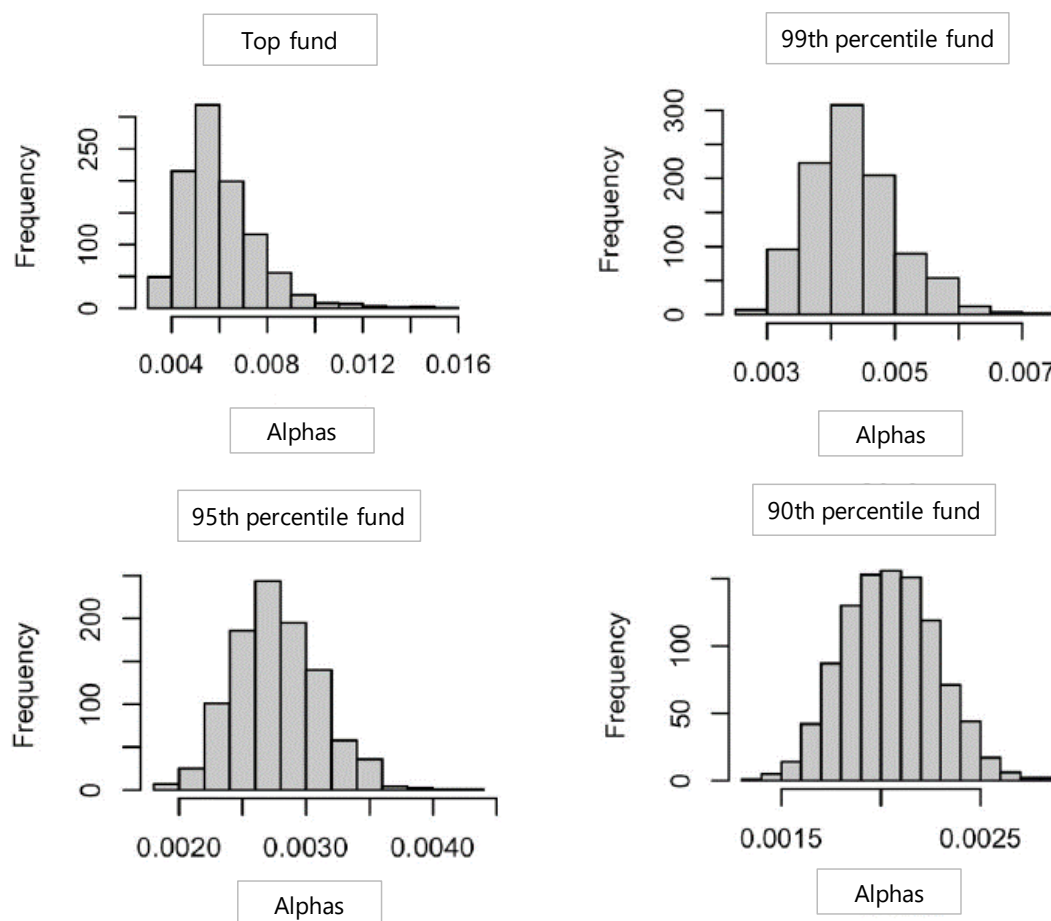
<b>Top fund</b>		<b>99th percentile fund</b>	
<b>Range</b>	<b>Frequency</b>	<b>Range</b>	<b>Frequency</b>
<0.000	0	<0.0025	1
0.000 - 0.002	0	0.0025 - 0.0030	8
0.002 - 0.004	42	0.0030 - 0.0035	77
0.004 - 0.006	535	0.0035 - 0.0040	238
0.006 - 0.008	307	0.0040 - 0.0045	277
0.008 - 0.010	91	0.0045 - 0.0050	221
0.010 - 0.012	17	0.0050 - 0.0055	107
0.012 - 0.014	4	0.0055 - 0.0060	46
0.014 - 0.016	3	0.0060 - 0.0065	19
0.016 - 0.018	1	0.0065 - 0.0070	4
>0.018	0	>0.0070	2
<b>Minimum</b>	0.002586	<b>Minimum</b>	0.0024707
<b>Maximum</b>	0.016429	<b>Maximum</b>	0.0073242
<b>Actual fund</b>	0.003006	<b>Actual fund</b>	0.0026798

<b>95th percentile fund</b>		<b>90th percentile fund</b>	
<b>Range</b>	<b>Frequency</b>	<b>Range</b>	<b>Frequency</b>
<0.00175	0	<0.001	0
0.00175 - 0.00200	5	0.00100 - 0.00125	0
0.00200 - 0.00225	48	0.00125 - 0.00150	7
0.00225 - 0.00250	155	0.00150 - 0.00175	93
0.00250 - 0.00275	297	0.00175 - 0.00200	327
0.00275 - 0.00300	261	0.00200 - 0.00225	362
0.00300 - 0.00325	147	0.00225 - 0.00250	174
0.00325 - 0.00350	61	0.00250 - 0.00275	32
0.00350 - 0.00375	21	0.00275 - 0.00300	5
0.00375 - 0.00400	5	0.00300 - 0.00325	0
>0.00400	0	>0.00325	0
<b>Minimum</b>	0.0018689	<b>Minimum</b>	0.0013673
<b>Maximum</b>	0.0039173	<b>Maximum</b>	0.0028860
<b>Actual fund</b>	0.0018364	<b>Actual fund</b>	0.0012900

For the distributions of the top fund and 99<sup>th</sup> percentile fund, the actual fund alpha falls within the distribution ranges. However, for the 95<sup>th</sup> percentile and 90<sup>th</sup> percentile fund distributions the actual fund alpha falls below the distribution ranges which suggests no skill was evident. Even though the top fund was within the alpha range, there was only one alpha lower than the actual fund alpha and for the 99<sup>th</sup> percentile fund there was only three alphas lower than the actual fund alpha. The level of skill at the total sample gross of fees level was therefore not evident or very low.

### 5.2.1.2 Total sample – Net of fees

Figure 5.2 Net of fees luck distributions for total sample



The net of fees distributions are similar in shape to the gross of fees distributions with a narrowing as the percentile decreases and more larger alphas at the top end of the distributions. This naturally further makes it even more challenging for funds to beat

the required returns (in this case to cover investment manager fees) based on the investment skill of the managers.

Table 5.2 Alpha frequency of luck distribution versus actual net of fees for total sample

<b>Top fund</b>		<b>99th percentile fund</b>	
<b>Range</b>	<b>Frequency</b>	<b>Range</b>	<b>Frequency</b>
<0.000	0	<0.0025	0
0.000 - 0.002	0	0.0025 - 0.0030	7
0.002 - 0.004	49	0.0030 - 0.0035	96
0.004 - 0.006	534	0.0035 - 0.0040	223
0.006 - 0.008	315	0.0040 - 0.0045	308
0.008 - 0.010	77	0.0045 - 0.0050	205
0.010 - 0.012	15	0.0050 - 0.0055	89
0.012 - 0.014	6	0.0055 - 0.0060	54
0.014 - 0.016	4	0.0060 - 0.0065	12
0.016 - 0.018	0	0.0065 - 0.0070	4
>0.018	0	>0.0070	2
Minimum	0.0031583	Minimum	0.0027609
Maximum	0.0157369	Maximum	0.0071532
Actual fund	0.0029534	Actual fund	0.0019010

<b>95th percentile fund</b>		<b>90th percentile fund</b>	
<b>Range</b>	<b>Frequency</b>	<b>Range</b>	<b>Frequency</b>
<0.00175	0	<0.001	0
0.00175 - 0.00200	7	0.00100 - 0.00125	0
0.00200 - 0.00225	33	0.00125 - 0.00150	6
0.00225 - 0.00250	180	0.00150 - 0.00175	92
0.00250 - 0.00275	280	0.00175 - 0.00200	334
0.00275 - 0.00300	258	0.00200 - 0.00225	365
0.00300 - 0.00325	161	0.00225 - 0.00250	176
0.00325 - 0.00350	60	0.00250 - 0.00275	24
0.00350 - 0.00375	16	0.00275 - 0.00300	3
0.00375 - 0.00400	3	0.00300 - 0.00325	0
>0.00400	2	>0.00325	0
Minimum	0.0018700	Minimum	0.0013495
Maximum	0.0043147	Maximum	0.0028825
Actual fund	0.0008086	Actual fund	0.0003555

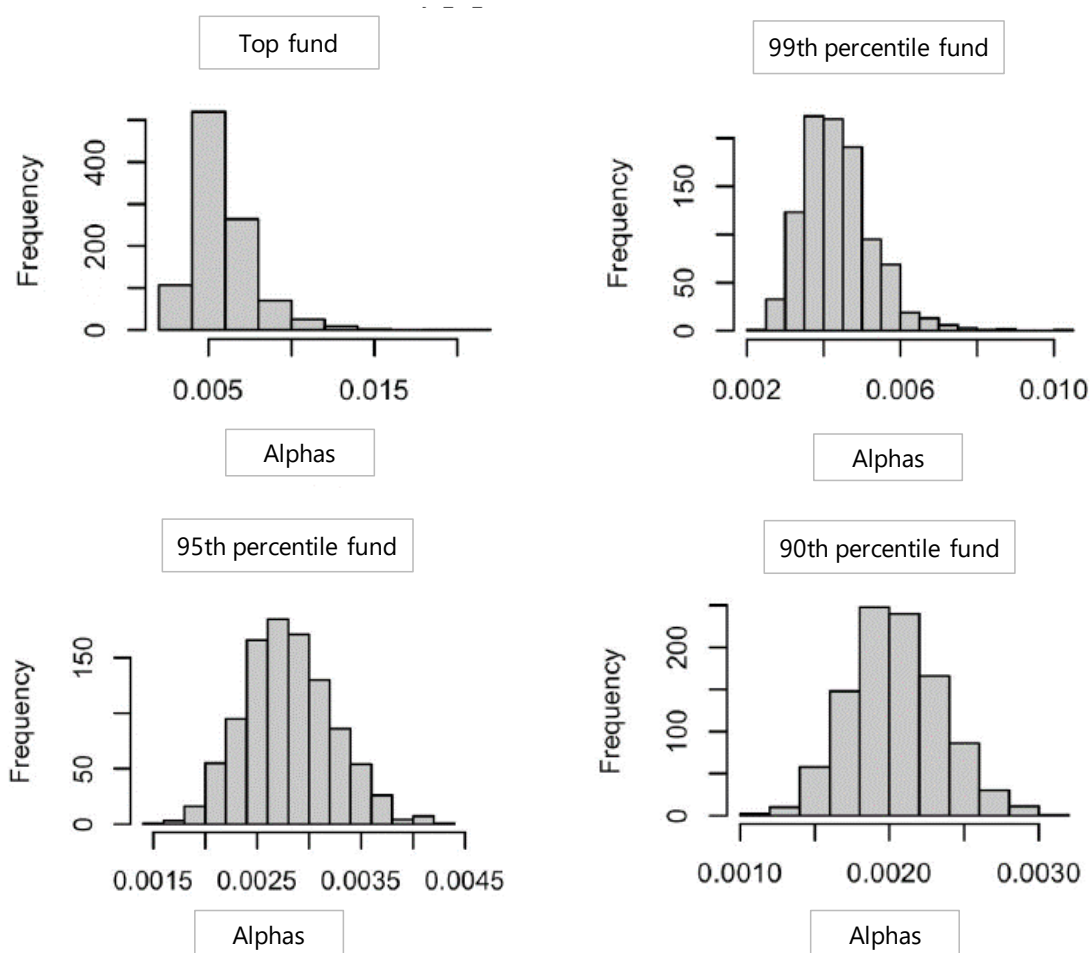
At all four percentile levels the actual fund alpha is lower than the minimum level of the luck distribution, which implies that all fund managers in the sample did not exhibit sufficient investment skill over the period under investigation to justify their fees.

### 5.2.2 Local only subsample

The gross and net of fees comparisons are shown separately. The charts that follow show the gross of fees distribution of the top fund, 99<sup>th</sup> percentile fund, 95<sup>th</sup> percentile fund and the 90<sup>th</sup> percentile fund for the luck distribution.

#### 5.2.2.1 Local only subsample – Gross of fees

Figure 5.3: Gross of fees luck distributions for local only subsample



There is very little symmetry in the distribution of the top fund in local only subsample with a few alphas thinly distributed on the upper end. The 99<sup>th</sup> percentile distribution is somewhat more symmetrical but also has a thinly dispersed number of alphas on the top end of the distribution. The 95<sup>th</sup> and 90<sup>th</sup> percentile distributions are

progressively more symmetric with the 90<sup>th</sup> percentile distribution having a similar dispersion of alphas on the bottom and top ends of the distribution. Again, it appears that the funds with the highest average returns, in this analysis the top fund and 99<sup>th</sup> percentile fund, have a number of outlying positive alphas that have increased the average return and made the top alphas more difficult to exceed.

Table 5.3 Alpha frequency of luck distribution versus actual gross of fees for local only subsample

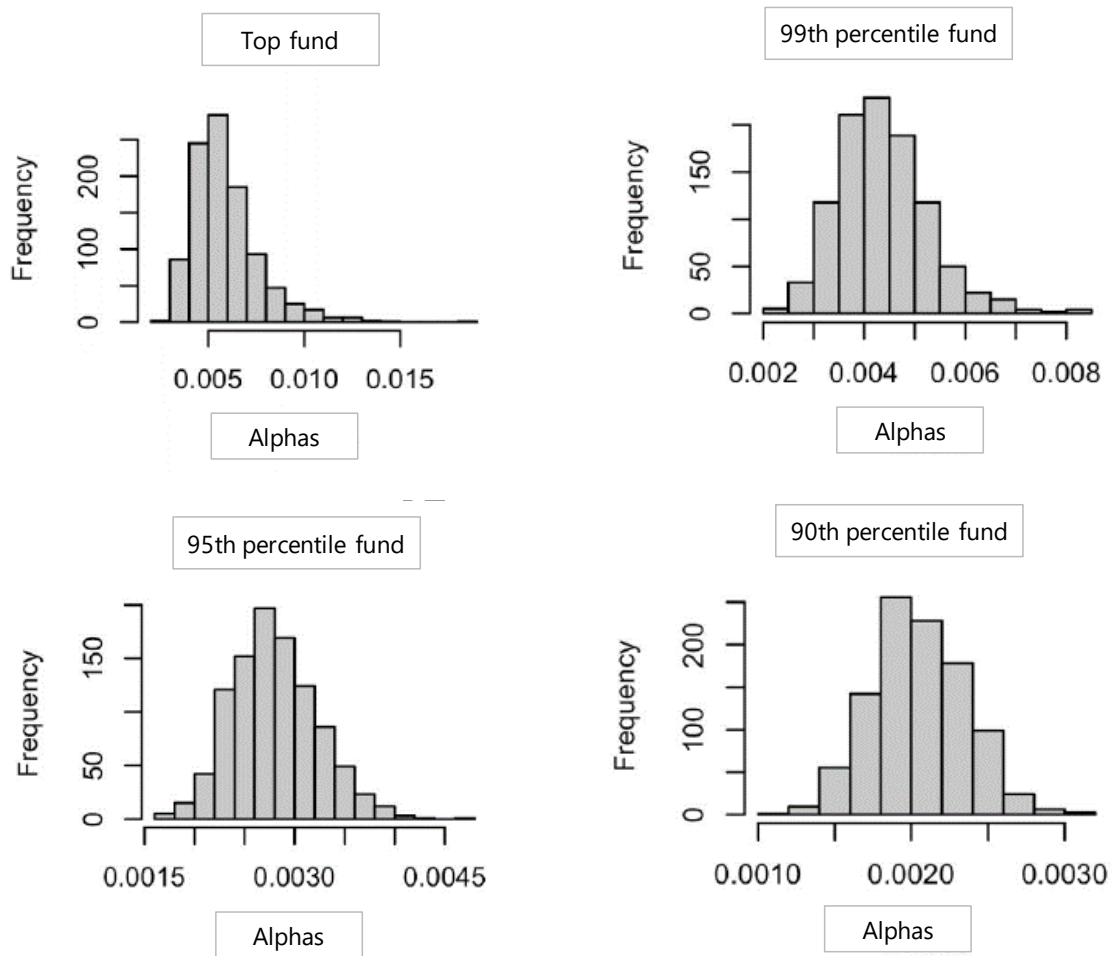
<b>Top fund</b>		<b>99th percentile fund</b>	
<b>Range</b>	<b>Frequency</b>	<b>Range</b>	<b>Frequency</b>
<0.002	0	<0.001	0
0.002 - 0.004	107	0.001 - 0.002	0
0.004 - 0.006	520	0.002 - 0.003	34
0.006 - 0.008	264	0.003 - 0.004	346
0.008 - 0.010	70	0.004 - 0.005	411
0.010 - 0.012	26	0.005 - 0.006	164
0.012 - 0.014	9	0.006 - 0.007	32
0.014 - 0.016	2	0.007 - 0.008	9
0.016 - 0.018	0	0.008 - 0.009	3
0.018 - 0.020	1	0.009 - 0.010	0
>0.020	1	>0.010	1
<b>Minimum</b>			
<b>Minimum</b>	0.0030081	<b>Minimum</b>	0.0024449
<b>Maximum</b>			
<b>Maximum</b>	0.0212837	<b>Maximum</b>	0.0101337
<b>Actual fund</b>			
<b>Actual fund</b>	0.0029626	<b>Actual fund</b>	0.0024859

<b>95th percentile fund</b>		<b>90th percentile fund</b>	
<b>Range</b>	<b>Frequency</b>	<b>Range</b>	<b>Frequency</b>
<0.00175	3	<0.001	0
0.00175 - 0.00200	17	0.00100 - 0.00125	2
0.00200 - 0.00225	68	0.00125 - 0.00150	15
0.00225 - 0.00250	159	0.00150 - 0.00175	155
0.00250 - 0.00275	220	0.00175 - 0.00200	294
0.00275 - 0.00300	225	0.00200 - 0.00225	286
0.00300 - 0.00325	153	0.00225 - 0.00250	170
0.00325 - 0.00350	95	0.00250 - 0.00275	58
0.00350 - 0.00375	46	0.00275 - 0.00300	19
0.00375 - 0.00400	6	0.00300 - 0.00325	1
>0.00400	8	>0.00325	0
<b>Minimum</b>			
	0.0014967	<b>Minimum</b>	0.0010279
<b>Maximum</b>			
	0.0042936	<b>Maximum</b>	0.0031063
<b>Actual fund</b>			
	0.0013775	<b>Actual fund</b>	0.0006369

Only the 99<sup>th</sup> percentile fund falls within the luck distribution with the top fund, 95<sup>th</sup> percentile fund and 90<sup>th</sup> percentile fund having an alpha below that of the respective luck distributions. The alpha of the 99<sup>th</sup> percentile fund was higher than only one of the alphas of the 99<sup>th</sup> percentile luck distribution.

### 5.2.2.2 Local only subsample – Net of fees

Figure 5.4 Net of fees luck distributions for local only subsample



The net of fees distributions appears more symmetrical than the gross of fees distributions and have more higher alphas than lower alphas for each of the four percentile ranges.

Table 5.4 Alpha frequency of luck distribution versus actual net of fees for local only subsample

<b>Top fund</b>		<b>99th percentile fund</b>	
<b>Range</b>	<b>Frequency</b>	<b>Range</b>	<b>Frequency</b>
<0.000	0	<0.00150	0
0.000 - 0.002	0	0.00150 - 0.00225	1
0.002 - 0.004	88	0.00225 - 0.00300	37
0.004 - 0.006	529	0.00300 - 0.00375	212
0.006 - 0.008	278	0.00375 - 0.00450	346
0.008 - 0.010	72	0.00450 - 0.00525	254
0.010 - 0.012	23	0.00525 - 0.00600	103
0.012 - 0.014	8	0.00600 - 0.00675	32
0.014 - 0.016	1	0.00675 - 0.00750	9
0.016 - 0.018	0	0.00750 - 0.00825	4
>0.018	1	>0.00825	2
<b>Minimum</b>	0.0029394	<b>Minimum</b>	0.0021599
<b>Maximum</b>	0.0181241	<b>Maximum</b>	0.0083173
<b>Actual fund</b>	0.0029534	<b>Actual fund</b>	0.0015096

<b>95th percentile fund</b>		<b>90th percentile fund</b>	
<b>Range</b>	<b>Frequency</b>	<b>Range</b>	<b>Frequency</b>
<0.00175	4	<0.001	0
0.00175 - 0.00200	16	0.00100 - 0.00125	1
0.00200 - 0.00225	70	0.00125 - 0.00150	26
0.00225 - 0.00250	164	0.00150 - 0.00175	140
0.00250 - 0.00275	218	0.00175 - 0.00200	296
0.00275 - 0.00300	229	0.00200 - 0.00225	279
0.00300 - 0.00325	146	0.00225 - 0.00250	181
0.00325 - 0.00350	94	0.00250 - 0.00275	65
0.00350 - 0.00375	36	0.00275 - 0.00300	10
0.00375 - 0.00400	18	0.00300 - 0.00325	2
>0.00400	5	>0.00325	0
<b>Minimum</b>	0.0016729	<b>Minimum</b>	0.0011518
<b>Maximum</b>	0.0047088	<b>Maximum</b>	0.0031639
<b>Actual fund</b>	0.0007346	<b>Actual fund</b>	0.0002119

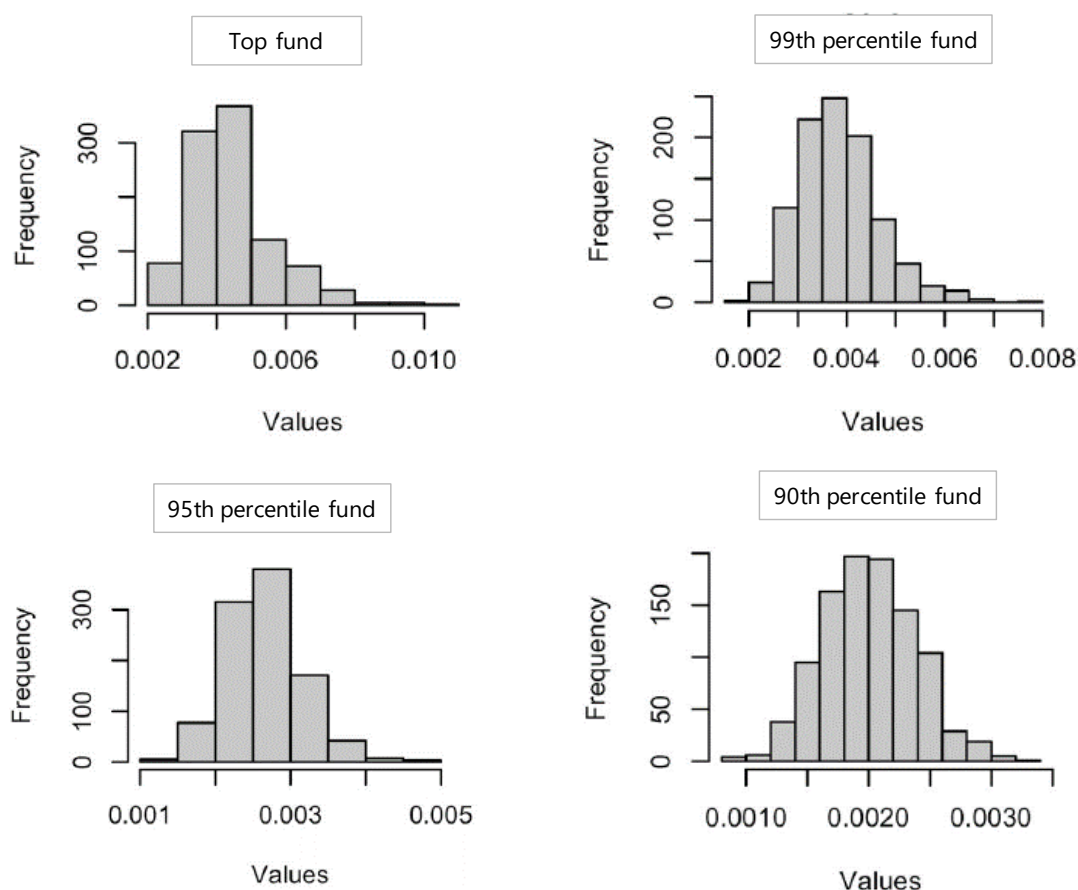
Only the top fund falls within the luck distribution, with the other funds all falling below the luck distribution. This is most likely as a result of the top fund having a lower than the average fee of the funds in the sample. The alpha of the actual top fund was greater than only two of the alphas in the top fund alpha distribution.

### 5.2.3 Global subsample

The gross and net of fees comparison are again shown separately. The charts that follow show the gross of fees distribution of the top fund, 99<sup>th</sup> percentile fund, 95<sup>th</sup> percentile fund and the 90<sup>th</sup> percentile fund for the luck distribution.

#### 5.2.3.1 Global subsample – Gross of fees

Figure 5.5 Gross of fees luck distributions for global subsample



The global gross of fees luck distributions are similar to the local only gross of fees luck distributions, with the 90<sup>th</sup> percentile distribution appearing more symmetrical with a similar spread of alphas on the bottom and top of the distribution. The top, 99<sup>th</sup> and 95<sup>th</sup> percentile distributions have a wider spread of higher than lower alphas.

Table 5.5 Alpha frequency of luck distribution versus actual gross of fees for global subsample

<b>Top fund</b>		<b>99th percentile fund</b>	
<b>Range</b>	<b>Frequency</b>	<b>Range</b>	<b>Frequency</b>
<0.001	0	<0.0020	2
0.001 - 0.002	0	0.0020 - 0.0025	24
0.002 - 0.003	78	0.0025 - 0.0030	115
0.003 - 0.004	321	0.0030 - 0.0035	222
0.004 - 0.005	368	0.0035 - 0.0040	248
0.005 - 0.006	121	0.0040 - 0.0045	202
0.006 - 0.007	72	0.0045 - 0.0050	101
0.007 - 0.008	28	0.0050 - 0.0055	47
0.008 - 0.009	5	0.0055 - 0.0060	20
0.009 - 0.010	5	0.0060 - 0.0065	14
>0.010	2	>0.0065	5
<b>Minimum</b>	0.0020227	<b>Minimum</b>	0.0019746
<b>Maximum</b>	0.0104562	<b>Maximum</b>	0.0075791
<b>Actual fund</b>	0.0030064	<b>Actual fund</b>	0.0027586

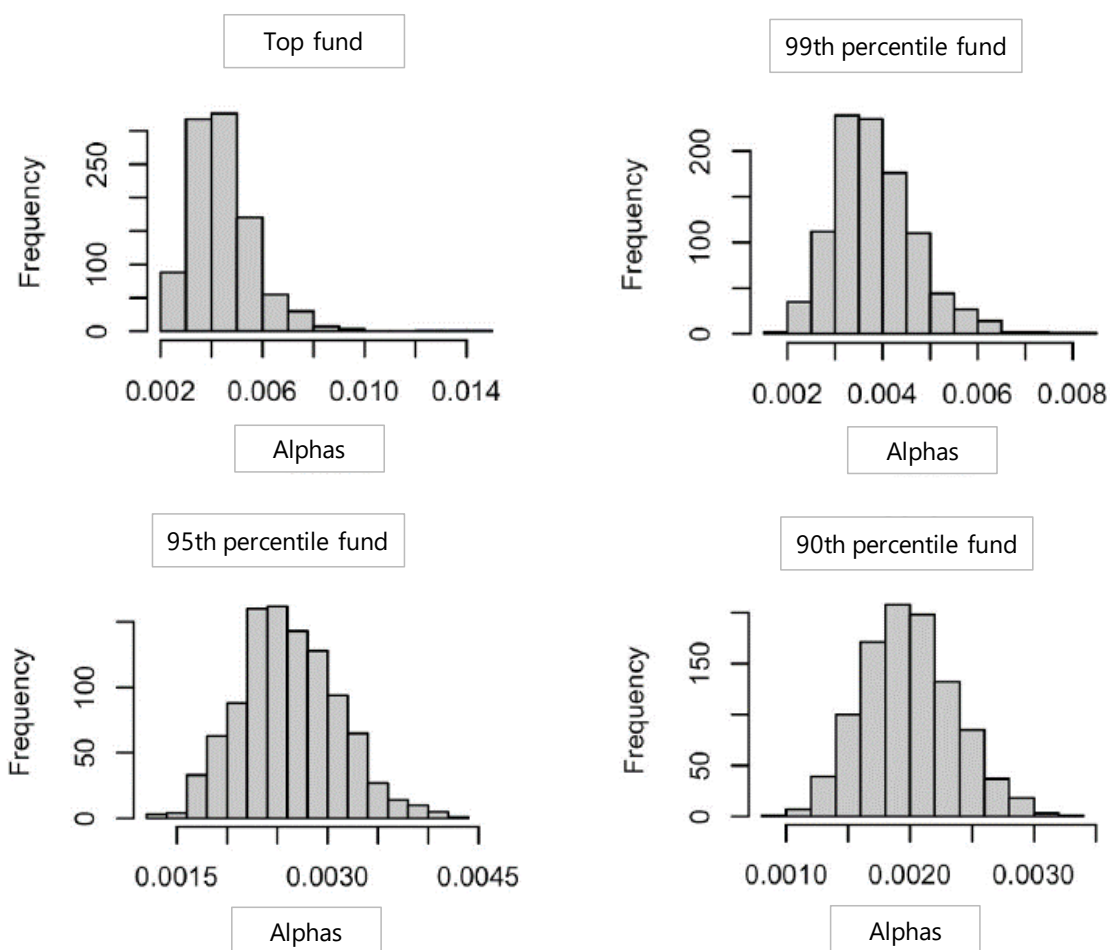
<b>95th percentile fund</b>		<b>90th percentile fund</b>	
<b>Range</b>	<b>Frequency</b>	<b>Range</b>	<b>Frequency</b>
<0.0005	0	<0.001	4
0.0005 - 0.0010	0	0.00100 - 0.00125	11
0.0010 - 0.0015	5	0.00125 - 0.00150	66
0.0015 - 0.0020	77	0.00150 - 0.00175	173
0.0020 - 0.0025	315	0.00175 - 0.00200	249
0.0025 - 0.0030	380	0.00200 - 0.00225	237
0.0030 - 0.0035	171	0.00225 - 0.00250	164
0.0035 - 0.0040	42	0.00250 - 0.00275	63
0.0040 - 0.0045	7	0.00275 - 0.00300	27
0.0045 - 0.0050	3	0.00300 - 0.00325	5
>0.0050	0	>0.00325	1
<b>Minimum</b>	0.0012670	<b>Minimum</b>	0.0008721
<b>Maximum</b>	0.0046455	<b>Maximum</b>	0.0032748
<b>Actual fund</b>	0.0024989	<b>Actual fund</b>	0.0017829

All four percentile funds are within each respective luck distribution range, which implies that a fund that held global underlying stocks, was able to deliver a greater

alpha relative to the luck distribution compared to funds that did not hold global stocks. For the top fund the actual alpha was greater than 79 of the 1,000 luck distribution alphas (7.9%), for the 99<sup>th</sup> percentile fund the actual alpha was greater than 73, for the 95<sup>th</sup> percentile fund the actual alpha was greater than 397 and for the 90<sup>th</sup> percentile fund the actual alpha was greater than 292 of the alphas in the respective luck distributions. While none of the actual alphas were greater than the highest alpha of the respective luck distributions a better indication of skill of evident with funds where a global allocation was used, especially for the 95<sup>th</sup> and 90<sup>th</sup> percentile funds.

### 5.2.3.2 Global subsample – Net of fees

Figure 5.6: Net of fees luck distributions for global subsample



The net of fees global distributions are similar to the gross of fees global distributions with only the 90<sup>th</sup> percentile distribution being close to symmetrical, particularly with

regard to a similar number of alphas spread across the bottom and top of the distributions.

Table 5.6 Alpha frequency of luck distribution versus actual net of fees for global subsample

<b>Top fund</b>		<b>99th percentile fund</b>	
<b>Range</b>	<b>Frequency</b>	<b>Range</b>	<b>Frequency</b>
<0.0000	0	<0.0020	2
0.0000 - 0.0015	0	0.0020 - 0.0025	35
0.0015 - 0.0030	88	0.0025 - 0.0030	112
0.0030 - 0.0045	502	0.0030 - 0.0035	239
0.0045 - 0.0060	311	0.0035 - 0.0040	235
0.0060 - 0.0075	74	0.0040 - 0.0045	176
0.0075 - 0.0090	18	0.0045 - 0.0050	110
0.0090 - 0.0105	4	0.0050 - 0.0055	44
0.0105 - 0.0120	0	0.0055 - 0.0060	27
0.0120 - 0.0135	2	0.0060 - 0.0065	14
>0.0135	1	>0.0065	6
<b>Minimum</b>	0.0020288	<b>Minimum</b>	0.0019822
<b>Maximum</b>	0.0140078	<b>Maximum</b>	0.0084252
<b>Actual fund</b>	0.0020951	<b>Actual fund</b>	0.0019433

<b>95th percentile fund</b>		<b>90th percentile fund</b>	
<b>Range</b>	<b>Frequency</b>	<b>Range</b>	<b>Frequency</b>
<0.00150	3	<0.001	1
0.00150 - 0.00175	28	0.00100 - 0.00125	14
0.00175 - 0.00200	72	0.00125 - 0.00150	74
0.00200 - 0.00225	123	0.00150 - 0.00175	188
0.00225 - 0.00250	203	0.00175 - 0.00200	249
0.00250 - 0.00275	195	0.00200 - 0.00225	238
0.00275 - 0.00300	160	0.00225 - 0.00250	144
0.00300 - 0.00325	116	0.00250 - 0.00275	62
0.00325 - 0.00350	59	0.00275 - 0.00300	26
0.00350 - 0.00375	23	0.00300 - 0.00325	3
>0.00375	18	>0.00325	1
<b>Minimum</b>	0.0012248	<b>Minimum</b>	0.0009050
<b>Maximum</b>	0.0042522	<b>Maximum</b>	0.0033666
<b>Actual fund</b>	0.0014094	<b>Actual fund</b>	0.0005567

The top fund and 95<sup>th</sup> percentile fund alphas are within the range of the respective luck distributions while the 99<sup>th</sup> percentile fund and 90<sup>th</sup> percentile fund alphas are below that of their respective luck distribution ranges. The top fund actual alpha was greater than two of the luck distribution alphas, while the alpha of the actual 95<sup>th</sup> percentile fund was greater than three of the 1,000 luck distribution alphas.

### 5.2.4 Summary of results

The table below summarises the results of the actual versus luck distributions by colour coding the outcomes, with red showing the actual being below the range of the luck distribution, orange being within the range of the luck distribution, and green being above the range of the luck distribution.

Table 5.7 Summary of actual versus luck distributions across the various variables investigated

		Top fund range			99th percentile fund range		
		Below	Within	Above	Below	Within	Above
Total sample	Gross of fees		Orange			Orange	
	Net of fees	Red			Red		
Local only subsample	Gross of fees	Red				Orange	
	Net of fees		Orange		Red		
Global subsample	Gross of fees		Orange			Orange	
	Net of fees		Orange		Red		

		95th percentile fund range			90th percentile fund range		
		Below	Within	Above	Below	Within	Above
Total sample	Gross of fees	Red			Red		
	Net of fees	Red			Red		
Local only subsample	Gross of fees	Red			Red		
	Net of fees	Red			Red		
Global subsample	Gross of fees		Orange			Orange	
	Net of fees		Orange		Red		

It is evident that there are no green cells, which means that there are no cases where the actual reference fund alpha has been higher than the range of alphas of the luck distribution for the corresponding percentile over the sample period. For the gross of

fees analysis there were seven occurrences where the actual alpha was within the range of luck distribution alphas and five occurrences where the actual alpha was below the range of luck distribution alphas. For the net of fees analysis there were three times that the actual alpha was within the range of luck distribution alphas and nine times that it was below the range. It is not surprising that the net of fees results show more alphas below the range of luck distribution alphas as fees are an additional level of return that needs to be captured by a fund in order to deliver a comparable alpha.

The global subsample had six of the eight actual alphas within the range of luck distribution alphas while the local only subsample had only two of the eight actual alphas within the range of luck distributions. Even in examples where the actual alpha was within the range of luck distribution alphas there were only a few cases where the actual alpha was greater than more than a handful of luck distribution alphas. This implies that even if there was some investment skill present it was not proportionately high compared to the expected levels of alphas.

A comparison of these outcomes to the existing literature on bootstrapping analyses of mutual fund risk-adjusted performance, show these results to be most similar to the Chinese equity funds analysis of Yang and Liu (2017) who found that no Chinese funds had an actual alpha greater than the comparative luck distribution alpha. This differs from the original US study by Kosowski et al. (2006) and the subsequent UK study of Cuthbertson, Nitzsche and O'Sullivan (2008), both of which found evidence of alphas above the luck distribution being present. It is notable that South Africa and China are emerging market economies, with a lower number of established fund management companies, but an increasing number of mutual funds coming to market. Inexperience among fund managers may explain their historical inability to clearly show skill above luck in these markets. In the US and UK markets, there are more fund management companies with long track records where a defined investment philosophy has been applied over many years, possibly resulting in a more consistent risk-return signature over time. The second similarity between this and the Chinese study is that the period

under investigation is later than the US and UK studies. Both the US and UK studies use mutual fund performance data from 1975 to 2002, while the Chinese study uses data from 2002 to 2013 and this study from 2006 to 2020. While this and the Chinese study does not match exactly in the period of the data, there is a reasonable overlap in the time period and no overlap between the US and UK data period compared to the Chinese and SA data periods. It may therefore be that a specific investment style was more conducive to active management outperformance over the earlier period compared to the later periods. The somewhat surprising aspect though is the expectation around market efficiencies. It is assumed that developed markets are more efficient than developing markets and that less efficient markets allow for the opportunity to outperform through more in-depth analysis as all information is not reflected as well or as quickly as in developed markets.

### **5.3 Conclusion**

Based on the bootstrapping analysis there is no evidence to suggest that fund managers displayed greater skill than a luck distribution of alphas would suggest over the period under investigation. There is, however, no conclusive evidence that no skill was evident, as seven of the 12 gross of fees actual alphas were within the range of luck distribution alphas. The level of skill, as indicated by the proportion of luck distribution alphas that were outperformed by the actual alphas, was generally low.

There appears to be a difference in the actual alphas of the local only subsample, compared to the global subsample, relative to the luck distributions. Funds that used global underlying holdings delivered greater alphas with all four gross of fees alphas being within the luck distribution range compared to the funds with no global holdings, where only one of the gross of fees alphas are within the luck distribution range. This sample period coincides with a period where the South African rand weakened from R6.28 to the US dollar in March 2006 to R17.50 to the US dollar in May 2020<sup>14</sup> which equates to a 7.5% depreciation per annum. This addition of global

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<sup>14</sup> Source: IRESS

underlying stocks would not only benefit from the exchange rate differential over the period but would add a potential diversification benefit to funds due to the broader investment universe globally and the possible inclusion of sectors not available in the South African market. The addition of global underlying stocks is therefore both an asset allocation and a stock selection decision which funds could have benefitted from compared to investing in the domestic universe only.

The reduction in the number of actual alphas that fall within the luck distribution alpha range as the percentile rank declines points to a small number of outlying funds that have delivered a high alpha over the period. This appears to be similar to the various luck distributions, but the actual alphas decline quicker than the luck distributions would suggest is expected.

## **Chapter 6 – Conclusion**

### **6.1 Background to the study**

This study tested whether South African equity general mutual fund managers showed skill in their stock selection based on the unit trust performance of domestic equity general funds over the period March 2006 to May 2020. This question is both academically significant and topical within the asset management industry and for South African investors in general.

The theoretical grounding of the study is the Efficient Market Hypothesis (EMH), a widely researched and debated area of study where one side in the debate argues that the EMH means that consistently outperforming the market is not possible, while the opposing camp uses empirical results to show that it is in fact possible. Some studies (e.g. Kremnitzer, 2012, and Kunene, 2017) argue that it is possible to outperform the market in emerging market economies (of which South Africa is one) mainly due to reasons around the dissemination of information across the market. This is also the start of the debate of whether manager skill can result in consistent outperformance of a passive benchmark.

Passive investing developed from the assumption that the EMH holds and that the average active fund will therefore underperform the index after costs. Passive investing, in its original form, holds equity weights in the same proportion as the index it replicates and therefore matches the index performance, save for a relatively small asset management fee due to no fundamental company analysis being required. Active management, which involves some analysis and holdings in different proportions to the index it is trying to outperform, charges higher fees, justified by the additional analysis required. Passive index investing has grown in popularity and assets under management have increased worldwide due to the lower fees the strategy charges and the predictability of returns relative to the stated benchmark. In addition, active investing has had difficulty in proving consistent outperformance or often needed long investment periods to attain meaningful outperformance. The highly

topical debate on whether active managers are able to sufficiently outperform (especially on a risk-adjusted basis), thus justifying their higher management fees, or whether investors should rather choose passive index trackers and have less of their long-term returns eroded by fees and be assured of a predictable return relative to an index, further contributes to the relevance of this study.

More recently passive fund management companies have added specific investment factors to their investment considerations. These factors are characteristics of the underlying companies they invest in, and may be based on current price, earnings projections or a relative consideration compared to a previous level, among others. Even though an active choice is made on which factors to replicate, the rules for the fund are hard-coded and the fund manager passively applies these rules. These funds have the potential to outperform passive index funds but may underperform when a factor is out of favour. The most popular and well-known examples of multi-factor models are the Fama and French 3-Factor Model, the Carhart 4-Factor Model, and the Fama and French 5-Factor Model. These models attempt to show that performance over a certain period can be explained by the specific factors included in the model, and that only alpha above what the model can explain can be regarded as an outsized gain (risk-adjusted outperformance) by the fund. There is empirical evidence to suggest that certain funds have been able to outperform (have a significant alpha) when a regression was conducted compared to the multi-factor models.

The second main question addressed by this study was that if some funds do outperform the index on a risk-adjusted basis, whether one can deduce from this that some fund managers outperform because of their skill, or by pure chance (*i.e.*, luck)? On this issue the literature also is quite divergent, with some researchers in no doubt that neither consistency nor skill was evident in stock selection (e.g. Lichtenstein, Kaufmann & Bhagat, 1999, and Yang & Liu, 2017), while others showed that it was indeed possible (e.g. Kosowski et al., 2006, and Cuthbertson, Nitzsche & O'Sullivan, 2008).

## 6.2 Focus of the study

In order to test the ability of domestic equity fund managers to outperform multi-factor models and then to test if any outperformance was due to skill or luck, two separate methodologies were used.

For the multi-factor analysis, the Fama and French 3-Factor, the Carhart 4-Factor, and the Fama and French 5-Factor models were used. In total 18 regressions were run, based on each of the three models, divided between a total sample, a local only subsample (funds only allowed to invest in South African listed equities), and a global subsample (funds allowed to also invest in some non-South African listed equities), with each of these regressions run on fund return data both gross and net of fees. The results were fairly consistent across the three samples, with the following notable findings:

- The gross of fees proportion of positive alphas was greater than the net of fees proportion of positive alphas. This is not surprising, as fees reduce fund performance and become more of a hurdle to actual experience returns as the fees increase.
- The average and median alpha for each of the 18 regressions were negative. This implies that even though some funds produced a positive alpha, the average fund was not able to outperform the factor model (*i.e.*, did not outperform on a risk-adjusted basis). Fees were not the only reason for this, as average performance gross of fees also did not outperform the factor models.
- The global subsample had a greater proportion of positive alphas than the local only subsample gross of fees, but not net of fees. This showed that on a gross of fees basis having global underlying holding added positively to fund performance. The reasons for this could be a greater universe to select stocks from, access to certain sectors not available in the domestic South African stock market and the rand weakness relative to developed market currencies over the period. However, as the net of fees performance was closely matched between the local only and

global subsamples, it follows that higher fees were charged by funds with a global allocation.

- The Carhart 4-factor comparison has the lowest proportion of positive alphas among the three models over all scenarios, and its distribution was narrower and taller around the mean with fewer outliers than the 3 and 5-factor models. The main difference between the models is the inclusion of momentum as a factor in the 4-factor model and not in the other models. It was also shown, based on the independent variables,<sup>15</sup> that momentum was the factor that contributed most to performance (highest mean and median) over the period of the study, as well as the highest positive outliers of the factors. This would imply that the Carhart 4-factor model was the most difficult to outperform over the period as momentum was the strongest contributor.

For the bootstrapping/resampling part of the study only the Carhart 4-Factor Model was used, as this was consistent with previous studies done in different countries. In addition, from the multi-factor regression analysis, the Carhart Model was the most difficult to outperform over the period and would therefore be the most stringent test of the three models.

For each fund a regression was performed based on the Carhart 4-Factor Model and the residuals were saved. These residuals were resampled with replacement 1000 times per fund to obtain a new distribution per fund. A new regression based on these returns was run irrespective of time to obtain the 1,000 alphas per fund for the luck distribution. The top fund, 99<sup>th</sup>, 95<sup>th</sup> and 90<sup>th</sup> percentile funds and distributions were recorded for comparison against the actual distributions.

Results were compared separately for the total sample, the local only subsample and the global subsample, as well gross and net of fees for top fund, the 99<sup>th</sup>, 95<sup>th</sup> and 90<sup>th</sup> percentile funds. In none of these 24 scenarios did the actual fund distribution have any alphas greater than the range of alphas for the luck distributions. In ten scenarios

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<sup>15</sup> See Table 3.2

the actual alpha was within the range of luck alphas and in 14 scenarios the actual alpha was below the range of alphas for the luck distribution. This implied that there was no conclusive evidence of skill among fund managers over the period. For the scenarios where the actual alpha was within the range of luck alphas the question of skill is inconclusive and could be as a result of randomness, and for the scenarios where the actual alphas were below the range of luck alphas fund performance was lower than what would be expected from simple random returns.

The implications of these results questions whether the higher fees charged by active managers in South Africa are justified if there is no strong evidence of skill for the vast majority of funds. However, even though skill was not statistically evident on average, there were funds that outperformed the benchmark and produced a positive alpha relative to the multi-factor model. If these funds can be identified and held for long periods, significant additional alpha can be achieved. A further question that could be raised is why all funds do not use the offshore allowance when the global subsample in the study produced superior alphas. While this may seem a reasonable question, there are number of arguments against this option. These include the resource requirements of having a team that can analyse the global stock universe, the idea that many equity general funds are used as building blocks so that investors can determine based on their requirements which and how much offshore investments would be appropriate, and the possible belief that offshore investing benefitted from rand weakness which may not repeat and could be a headwind for global investing going forward.

### **6.3 Limitations and considerations**

With any study there are limitations that need to be noted as they may have an influence, or need to be considered to provide context to, the results. The following limitations and considerations were identified for this study:

- The sample size of 179 funds was relatively small compared to the previous studies conducted in other countries. This is as a result of the smaller size of the asset

management industry in South Africa. However, while a larger sample is helpful for analysis, this sample size was acceptable for the statistical analysis required.

- The benchmark used throughout the study was the FTSE/JSE All Share Index, which is the widely quoted domestic equity index, but is not necessarily the index that most equity funds are benchmarked against. In South Africa the stock exchange has gone through periods of high concentration of the largest listed stocks. In 2007/2008 Anglo American and BHP Billiton together made up more than a third of the index (Raubenheimer, 2010) and more recently Naspers has made up more than a quarter of the index (Omar, 2017). The market has therefore changed the primary equity benchmark from time to time. The most widely implemented changes were a trend away from the All-Share Index to the SWIX Index around 2007 and more recently, as a result of the concentration of Naspers, to the Capped SWIX Index in 2017, which limits any single stock exposure to a maximum of 10%.
- Historical fund performance is time dependent. This study used performance data from March 2006 to May 2020 due to some of the required data only being available from the start of this period. Over certain periods some funds perform better due to market conditions then being more favourable to their particular investment philosophies. Empirical evidence indicates that value investing has been out of favour in South Africa over the past decade at least (Shaw, 2020), and that funds that followed that philosophy would generally have experienced relative underperformance compared to funds with different investment philosophies more suited to the prevailing market conditions. Highly concentrated indices like the JSE All-Share Index tend to favour momentum strategies, as the biggest stocks become bigger as they become more concentrated.
- Relative performance is model dependent. In this study the Carhart 4-Factor Model was used in accordance with previous similar studies in other markets.

## **6.4 Suggestions for future research**

Suggestions for future research, which would build on and improve this study, include to use a longer or different time period where momentum is not as strong a factor, but this will only be possible once sufficient additional data is available. This may change the relative alpha of the actual fund compared to the luck distribution. Another possibility, which will not include having to wait for more data to become available, would be to test relative to investment style. This would differentiate between value, growth, momentum etc., and may show how certain strategies benefit from market conditions at that time.

An additional consideration could be to match each fund to its official benchmark to gauge performance relative to this hurdle which fund managers are managing against. Further, additional multi-factor models could be explored for the bootstrapping resampling, especially the Fama and French 5-Factor Model, for which the additional two factors are more company and less price focused.

A more significant extension of this study could involve an attribution analysis across multi-asset funds, separating the stock selection from the asset allocation, and gauging whether asset allocation decisions add more value, even if skill in stock selection is not evident. This could assist in resource allocation in fund management investment teams and where to focus research time.

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