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Norwegian Global Mutual Funds:

An Empirical Study of Active Management and Fund Performance

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Abstract

The following paper uses a dataset free of survivorship bias in the period of 2009 - 2017. The purpose of this research is to investigate the performance of open end Norwegian global mutual funds. We start by first applying tracking error and R^2 to measure the activeness, and the results indicate that 22.73 % of the funds are closet indexers. Secondly, we evaluate their performance in subject to their benchmark by looking at the alpha generated from various factor models. We find that some managers are able to beat their benchmark gross of fees, but we find no significant evidence of outperformance net of fees. To be able to distinguish skill from luck we utilize a bootstrap procedure where we evaluate the distribution of the cross section of alpha if every fund had zero true alpha by construction. We find that on average fund managers are not able to deliver alpha, but that there exists some evidence of a nonzero true alpha in the extreme left and right tails when using gross returns.

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1.0 Introduction

Individual investors that do not have the time, skill or resources to generate excess return in financial markets, have the opportunity to utilize economies of scale if they let professionals manage their money. When investors want to invest in mutual funds, perhaps the biggest question they must consider is whether they ought to invest their money into passive index funds or to pay the extra dollar for someone to actively manage their money. Advocates of passive portfolio management believe that the market is efficient, meaning that a manager that continuously tries to beat the market will fail as the market already has incorporated all available information that is needed to obtain an edge. On the other side, we find advocates of active portfolio management. Being active means that they believe markets are not efficient, and that deviating from the passive management strategy would generate superior returns. While a passive strategy will only be able to generate the market return of the investment before costs, the active strategy must generate a higher return than the benchmark for the investor to obtain a better trade-off (Sharpe, 1991). This is a result of the compensation the managers require, both for the time they use to locate winning strategies, and other fees in regard to being an active fund. In many cases the trade-off between cost and return does not lean in favor of an active management strategy.

In this paper we examine the performance of Norwegian based global mutual funds with portfolios that primarily consist of international equities. These funds are what is known as global funds and provide investors with different risk profiles and investment strategies as opposed to domestic funds. An investors choice to invest in global funds could be many, but the main mindset of every investor is obviously to maximize returns, given the risk they are willing to undertake. By investing globally, they could seek out different ways to earn high returns, as well as benefit from the global diversification they get with it. According to the Norwegian Fund and Asset Management Association, as of 2016 the total capital under management in Norwegian global mutual funds amounted to NOK 210 Billion - an amount nearly twice the size of mutual funds that solely consists of Norwegian securities. We find this to be an intriguing fact and will therefore study Norwegian based global funds.

We also see this as our contribution to the literature, as there to our knowledge have not been conducted any extensive research on the performance of Norwegian global mutual funds to date.

A recent study conducted by S&P Dow Jones Indices in 2016, showed that 85 to 90 percent of all actively managed funds in the US and funds that invest globally, persistently failed to beat their benchmark index targets over one-year, five-year and ten-year periods. Using alpha, we will evaluate if this is also the case in Norwegian based mutual funds over a time period ranging from the start of 2009 until the end of 2017. We will answer this question in two parts. Firstly, we generate an equally weighted portfolio of all funds in our sample to account for survivorship bias, and to figure out what multifactor model that will produce the most reliable results. Secondly, we evaluate the performance of each fund individually by conducting a series of time-series regressions on each fund, before and after fees. By doing this we are able to evaluate and compare the alpha generated from each fund with each other, and finally rank the funds from best to worst.

In recent years it has come to light that numerous of funds that claim to be actively managed in fact only invest in accordance to the benchmark index. This is known as "closet indexing", and is a tool that funds use to lure money from customers as they charge high operating expenses for "actively managing" their money, when in fact they are not. This is a topic that is of current interest in Norway today as Norway's largest bank, DNB, was in late 2017 targeted by a class action on behalf of 180,000 customers, accused of not actively managing their funds.[1] As a consequence of this, we want to investigate whether Norwegian based global mutual funds are being as actively managed as they claim to be. We examine this by evaluating each fund's respective R^2, and by applying the modified standard deviation measure; Tracking Error. We decided to solely look at funds that are categorized as active in their prospectus, hence omitting all passive mutual funds and index funds from our analysis.

A key issue when accessing mutual fund performance is to distinguish whether their ability to beat the market is due to skill or luck, or consequently those that cannot generate abnormal return is due to bad luck or lack of skills in general.

[1] DNB was in the end not found guilty, as the court felt that the Shareholders did not have any legal claim to any higher degree of active management than they had already received. (www.E24.no).

We examine this by performing 10,000 bootstrap simulations, using the same methodology as Kosowski et al. (2006) and Fama and French (2010). This enable us to distinguish managers skill level from luck in the cross-section of alpha.

From our analysis, we find that closet indexing do in fact exist among Norwegian based global mutual funds. When studying performance of an equally-weighted portfolio, we find that on average, Norwegian mutual fund managers are not able to outperform their benchmark when applying the Fama and French (2014) five-factor model. The results hold both before, and after fees are incorporated. The results are similar when we study individual fund performance, but it shows that some managers are able to beat their benchmark gross of fees. The bootstrap analysis show that the average mutual fund investor does not have enough skills to be able to generate abnormal risk-adjusted returns both net and gross of fees.

The rest of the thesis is organized as follows: Section 2 provides a review of prior research on similar studies while section 3 presents related theory. Section 4 and 5 describes the methodology and data used. Section 6 provides the empirical results and interpretation. Section 7 concludes the study.

2.0 Literature review

The question whether active portfolio managers have the ability to outperform the benchmark has been a widely discussed topic for a long time, and have generated a lot of controversy over the years. There is a lot of prior research, and the results are mixed. In this section we will present prior research that is of relevance to our research questions.

In his paper *"The performance of mutual funds in the period 1945 - 1964"*, Michael C. Jensen (1968) introduced alpha as a measure of mutual funds' performance. By using alpha, he was able to measure the difference in performance of a mutual fund compared to a passive benchmark with the same risk. 115 mutual funds were included in his investigation, and he concluded that those funds on average were not able to outperform the market index. The results show that his conclusion holds both before and after management expenses.

Malkiel (1995) studied mutual fund returns from 1971 to 1991. After analyzing returns from all funds, Malkiel concluded that mutual funds underperformed the market, both before and after management expenses. He was able to obtain measures of survivorship bias, which is the bias you get from only including surviving funds, and estimated it to be more substantial than previously noted. Malkiel further suggests that previous studies who found active management to be superior, were likely to be influenced by survivorship bias.

Daniel, Grinblatt, Titman and Wermers (1997) conducted a study that measured whether mutual fund managers pick stocks that outperform simple mechanical strategies, such as book-to-market and momentum. They included a new measure that matched the characteristics of the component shares in the funds under evaluation. Their results suggest that some mutual funds were able to identify over-performing stocks, but that the outperformance was approximately equal to the management fees. They also found that more risky funds that invest in growth stocks, have the highest performance, but also the highest cost. This is consistent with the findings of Grossman and Stiglitz (1980) who found that informed investors only outperform the market to the degree that they are able to earn back their fees.

Carhart (1997) use a dataset free of survivorship bias that includes all diversified equity funds in the period from January 1962 to December 1993 to examine the persistence in mutual fund performance. In his study he expanded the already established 3-factor model by Fama & French (1993) by adding the momentum effect of stocks as an explanatory variable by Jegadeesh and Titman (1993), an effect based on that high performers probably will be high performers in the near future. He concludes that the profit gained by following a momentum strategy will be covered by the transaction costs for most mutual funds, excluding the top- decile that overperform and the bottom- decile that underperform. He also finds very slim evidence that funds with high 4-factor alpha have over-average high alpha and expected return in subsequent periods, so that there would exist short term persistence explained by skilled, or informed mutual fund managers.

Bogle (2002) states that in most cases the benchmark index will perform better than actively managed portfolios. In his paper *"An Index Fund Fundamentalist"* from 2002, he looked at the fund performance in all the "Morningstar style boxes", a matrix that consist of small, mid and large-capitalization on the y-axis and value, growth and blend-composition on the x-axis. Here he showed to a previous study he conducted over a 5-year period from 1992 to 1996, where he found that in terms of risk-adjusted return, index funds were superior in all except small-cap growth stocks. He then went on to conduct the same study but now for a ten-year period ending in 2001. The result was according to him not surprisingly nearly the same, whereas now not just the eight boxes, but instead all of the nine style boxes provided superior returns in favor of index funds.

Looking into studies related to the performance of global mutual funds; Cumby and Glen (1990) conducted a study of global mutual fund performance in the U.S, with a goal to evaluate how well U.S. global mutual funds performed in comparison to domestic and global benchmark indices. 15 U.S. based global funds were used in their analysis, with The Morgan Stanley World Index and the Morgan Stanley U.S. Index used as comparable benchmarks. They used alpha to measure portfolio performance from 1982 to 1988. An interesting finding from their study were that fund managers in general are timing perverse, i.e. that they take on more risk when the markets are falling and decrease their risk exposure when the markets are rising. The main takeaway from their analysis, however, is that US global funds overall did not manage to outperform their respective benchmark over the six-year period. Droms and Walker (1994) increased their sample of funds and the time period evaluated from previous studies with a goal to obtain more reliable results. They implemented a cross-sectional/time-series regression approach, where they found the alpha in global mutual funds to not be significantly different from zero. On the other hand, they found evidence that global funds do provide benefits from global diversification, where an international portfolio's rate of return commensurate with their exposure to risk.

Shukla and Singh (1997) wanted to evaluate the performance of U.S based global funds as opposed to U.S based domestic funds. Their findings suggest that the U.S. based global fund performance is superior to the global benchmark (MSCI). However, their findings further suggest that an U.S based investor would get even better off by investing domestically, as it provides better risk adjusted returns. On the other hand, they set forth that if you are able to forecast in which months that the U.S domestic market will perform poorly, one can benefit, as global funds predominantly did provide superior returns during these months.

In more recent years Amihud and Goyenko (2013) conducted an analysis that introduced R^2 as an alternative performance measure that does not rely on holding data. They use both the factor models of Fama & French (1993) and Carhart (1997) to evaluate whether R^2 is able to predict alpha. They emphasize on how well R^2 is able to include several risk factors, and find support for their hypothesis that R^2 in fact is a sufficiently good predictor of performance.

Petajisto (2013) use active share and tracking error to sort mutual funds into various categories of active management. Petajisto find that the most active stock pickers outperform their benchmark indices even after fees, while the closet indexers underperformed. He further finds that closet indexing has increased in popularity since 2007, and as of 2013 it accounts for about one-third of all mutual funds in the US.

Kosowski et. al (2006) performed a new bootstrapping technique in order to distinguish whether those fund managers that are able to provide abnormal return are doing so as a result of skill or pure luck. They examine the performance of U.S. open-end, domestic equity mutual funds over the time-period 1975 - 2002. Their findings suggest that the majority of fund managers are not able to provide sufficient returns to cover cost. Conversely, their findings differ from previous studies in showing that a sizable minority of the fund managers' superior alpha actually persist.

Fama and French (2010) conducted a similar study to Kosowski et al. (2006) comprising of U.S. mutual funds in the time-period 1984 - 2006. Their aim was also to measure skill versus luck, but instead of simulating each fund's return independently, they modified the procedure to jointly sample fund returns instead. The main motivation of their study was to answer the question of what distribution of the cross section of alpha in active funds that would be expected if the true alpha is zero in every fund. This was done as opposed to Kosowski et al. (2006) both net and gross of fees. Net of fees they find little evidence that supports that fund managers are able to generate returns sufficient to cover their costs. On the other hand, looking at the results from the bootstrapping procedure, gross of fees, there is evidence of inferior and superior performance, hence a nonzero true alpha estimate.

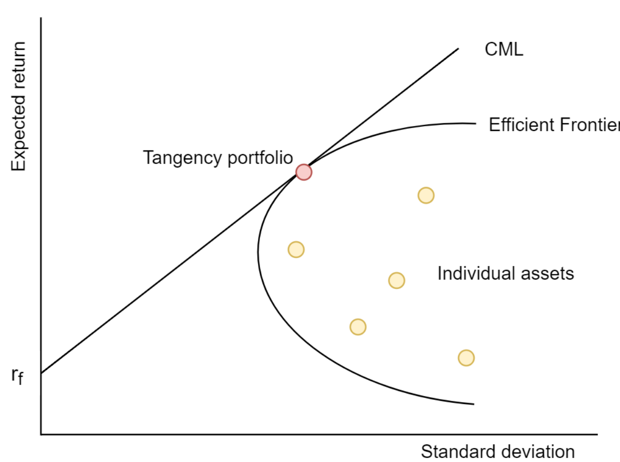
Sørensen (2009) conducted a study on all mutual funds that have existed on the Oslo Stock Exchange between 1982 and 2008. His dataset therefore ended up being free of survivorship bias, where his result shows a statistically significant difference in active return on -3.1 % by funds that ceased to exist and those active in 2009. He finds the alpha to be indistinguishable from zero in actively managed funds. He therefore concludes that there is little to no evidence of any abnormal performance of actively managed funds in respect to benchmark returns, using the Fama and French (1992) three-factor model.

Most of the prior research on mutual fund performance is conducted on U.S. mutual funds, while in more recent years some have studied the Norwegian fund market. There is no prior research on Norwegian based global funds, which is the scope of this thesis. However, we expect to get similar findings as the studies conducted abroad. Even though results from prior research are mixed, the research in favor of a passive strategy outweighs the research in favor of an active strategy. Based on previous literature we also expect closet indexing to exist among Norwegian based global funds.

3.0 Theory

Modern portfolio theory (MPT) was introduced by Harry Markowitz (1952). According to MTP, it is possible to construct an efficient frontier which is a combination of individual assets that maximize return for a given level of risk. MPT assumes investors are risk-averse, meaning that they for a given level of return prefer a less risky portfolio to a riskier one.

Figure 1: Efficient Frontier



The tangency line or the capital market line (CML) graphs risk premiums of efficient portfolios as a function of standard deviation. CML is defined as:

$$r_p = r_f + \sigma_p \frac{r_m - r_f}{\sigma_m} \tag{1}$$

The equation says that the return of a portfolio is equal to the risk-free rate plus a risk premium.

The capital asset pricing model (CAPM) by Sharpe (1964) and Lintner (1956) is an extension of MPT, and describes the relationship between risk and return for a given asset. While MPT is only able to price a portfolio, CAPM can price any asset. The CAPM equation is defined as:

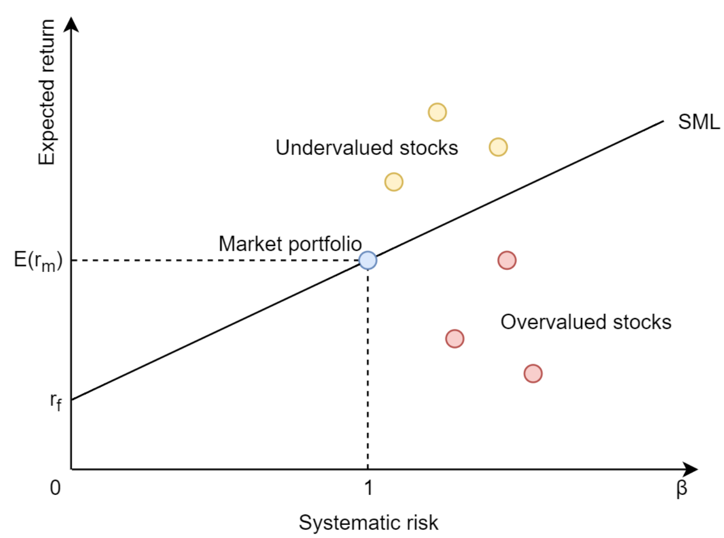
$$r_i = r_f + \beta_m \,(r_m - r_f) \tag{2}$$

The equation implies that the expected return for an asset is equal to the risk-free rate plus the market premium times the beta, which is given by:

$$\beta_m = \frac{Cov\,(r_i , r_m)}{\sigma^2 (\,r_m\,)} \tag{3}$$

Beta is the sensitivity of the asset to the market and indicates how much the asset is exposed to market risk. Higher value of beta indicates higher volatility.

Figure 2: Security Market Line



The security market line (SML) graphs risk premiums of individual assets as a function of beta. In market equilibrium, all assets that are fairly priced will lie on the SML. Assets that deviates from the SML are subject to mispricing. If the asset is overpriced it will provide an expected return less than what the SML predicts given its beta, and will hence lie below the SML. CAPM also states that investors should only be rewarded for systematic risk, which is market risk that cannot be diversified away.

Since we in this thesis will measure the performance of Norwegian based global mutual funds and compare it to their benchmark index, we find it necessary to define active and passive portfolio management. Bodie, Kane and Marcus (2014) defines passive portfolio management as buying a well-diversified portfolio to mirror a market index, without attempting to search for mispriced securities. Active management on the other hand is the attempt to improve performance either by identifying mispriced securities or by forecasting broad market trends.

Bodie, Kane and Marcus (2014) further defines an active portfolio in the context of the Treynor-Black model, as a portfolio that is formed by mixing analyzed stocks of perceived non-zero alpha values. This portfolio is ultimately mixed with the passive market-index portfolio.

When defining active and passive management styles, it *must* be according to Sharpe (1991) the case that: (1) before cost: The return on the average actively managed dollar will equal the return on the average passively managed dollar and (2) after cost, the return on the average actively managed dollar will be less that the return on the average passively managed dollar. Sharpe therefore categorizes the markets as efficient, so that the passive investment strategy would include all possible investment opportunities and entails that all investors have the same objectives.

The Efficient Market Hypothesis (EMH) was first introduced by Fama (1969). He defined an efficient market as a market in which prices fully reflects all available information. The EMH is normally divided into three different forms. The weak form hypothesis states that stock prices already reflect all information on market trading data, such as the history of past prices and trading volume. The semi-strong form hypothesis states that stock prices reflect all publicly available information. Finally, the strong form hypothesis states that stock prices reflect all information that is relevant to the firm, even information that is available only to company insiders.

"Proponents of the efficient market hypothesis believe that active management is largely wasted effort and unlikely to justify the expenses incurred. Therefore, they advocate a passive investment strategy that makes no attempt to outsmart the market" (Bodie, Kane & Marcus, 2014).

If the efficient market hypothesis holds, investors would be unable to outperform the market through mispriced securities. It would therefore, according to EMH, be more rational to invest in low cost index funds rather than actively managed mutual funds.

4.0 Methodology

4.1 Model Selection

In this section, we discuss the different multifactor models used to explain mutual fund returns and to what degree they are able to evaluate performance. The main purpose of using factor models in the evaluation of mutual fund performance is to compare actual fund returns with the return generated from the respective factor model. By doing this you are able to determine to what degree the exposure of each included risk factor attributes to the performance. The return that is not accounted for in the model is captured in the intercept; formerly known as alpha (*α)*. To obtain the alpha intercept, we run a series of time-series regression on each individual fund, as well as on an equally weighted portfolio of all funds that we included in the sample.

Alpha is today a widely used measure of fund performance, developed by Jensen (1968), with the purpose of evaluating whether investors are rightfully compensated for taking on increased volatility risk. A statistically significant alpha would suggest that a fund is able to generate abnormal return. The alpha equation from a single-factor model can be illustrated by:

$$\alpha_i = (r_i - r_f) - \beta_m(r_m - r_f) \tag{4}$$

where a positive α indicate that the fund delivered superior risk-adjusted return while a negative α indicate that the fund performed worse than the market.

As the alpha generated from this single-factor model is only exposed to the market proxy, it would not account for what has later been proven to be reliable market anomalies in explaining fund performance, such as book-to-market and momentum factors. Consequently, the factor models we chose to investigate is the well-established Fama and French (1992) three-factor model and Carhart's (1997) four-factor model, as well as the fairly new Fama and French (2014) five-factor model.

4.1.1 Three-factor model

The three-factor model by Fama and French (1992), is an extension to the well-known CAPM, that was developed by William Sharpe (1964) and John Lintner (1956). It was developed because overperformance of the small minus big (SMB) and the high minus low (HML) factors was not accounted for in the CAPM. SMB aims to capture the effect of that small-cap stocks generate larger returns than the CAPM predicts, while HML accounts for the anomaly that firms with a high book to market ratio tend to outperform firms with a low book to market ratio. The Fama and French 3-factor model can be illustrated as follows:

$$r_i - r_f = \alpha_i + \beta_m(r_m - r_f) + \beta_{SMB}SMB_t + \beta_{HML}HML_t + \varepsilon_i, \quad (5)$$

where r_i is the return on a portfolio or security i for period t, r_f is the risk-free return, r_m is the return on the value-weighted market portfolio, SMB_t is the return on a diversified portfolio of small stocks minus the return on a diversified portfolio of big stocks, HML_t is the difference between the returns on diversified portfolios of high and low B/M stocks, e_{it} is a zero-mean residual.

4.1.2 Four-factor model

The four-factor model developed by Carhart in 1997 is an extension to the Fama and French (1992) three-factor model. Carhart decided to include a momentum factor that aimed to capture the anomaly that past winners will continue to perform good and that past losers will continue to perform bad. The model can be illustrated as follows:

$$r_i - r_f = \alpha_i + \beta_m(r_m - r_f) + \beta_{SMB}SMB_t + \beta_{HML}HML_t + \beta_{WML}WML_t + \varepsilon_i \quad (6)$$

where r_{it} is the return on a portfolio in excess of the risk-free rate, and WML_t is the return on a diversified portfolio for one-year momentum in stock returns.

4.1.3 Five-factor model

In 2014 Fama and French found it reasonable to expand the three-factor model of Fama and French (1992), by adding two new quality factors to the equation; investment and profitability factors. These two factors aim to account for the fact that securities of firms with high operating profitability perform better, and that securities of firms with a high total asset growth tend to provide below average return. The model can be illustrated as follows:

$$r_i - r_f = \alpha_i + \beta_m(r_m - r_f) + \beta_{SMB}SMB_t + \beta_{HML}HML_t + \beta_{RMW}RMW_t + \beta_{CMA}CMA_t + \varepsilon_i \qquad (7)$$

where RMW_t is the difference between the returns on diversified portfolios of stocks with robust and weak profitability, and CMA_t is the difference between the returns on diversified portfolios of low and high investments stocks.

4.2 Measuring the activeness of funds

When we are going to assess if a fund is being actively managed or not, we have to calculate to what degree the active portfolio deviates from its comparable benchmark index (Sørensen, 2009). Two of the most renowned measures for this purpose is the R^2 measure and the tracking error measure.

4.2.1 R^2 measure

The R^2 measure that ranges from 0 to 1 is the percentage of variability in fund performance that is explained by variability in benchmark performance. A mutual fund that does not deviate from the benchmark, typically an index fund, would have a R^2 close to 1. Following this analogy, an active mutual fund would need a considerably lower R^2 to be considered to be actively managed. The R^2 measure is based on the following regression:

$$r^2 = \frac{\sum_{i=1}^{n}(\hat{y}_i - \bar{y})^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}. \qquad (8)$$

4.2.2 Tracking Error

Tracking error is a measure of the volatility of the difference in return between a fund and its benchmark. It gives you an indication of how closely a fund follows the benchmark. High tracking error indicates that the portfolio deviates a lot from the benchmark, while low tracking error indicates that it follows the benchmark closely. Ideally a portfolio manager would want to have a combination of low tracking error and high excess return, since tracking error in some ways is a measure of excess risk, but a high tracking error could also mean that the portfolio has outperformed its benchmark. The tracking error measure can be illustrated as follows:

$$TE = \sqrt{\frac{\sum_{i=1}^{n}(R_P - R_B)^2}{N-1}} \tag{9}$$

where R_P is the return of manager or fund, R_B is the benchmark return and N is the number of return periods in the sample.

4.2.3 Range

The European Securities and Market Authority (ESMA) have provided a range to the extent of funds potentially being closet indexers. They define the term as the practice of fund managers that are claiming to actively manage their portfolios, when in reality it stays close to a benchmark. ESMA classify funds with a tracking error lower than 4 % and a R^2 of more than 95 % as potentially being closet indexers. Funds with R^2 above 95 % or tracking error below 4 % will therefore be classified as closet indexers in our analysis.

4.3 Measuring skill vs. luck

4.3.1 Bootstrap

In 2006, Kosowski et al. were the first using a bootstrap method to distinguish skill from luck in mutual funds' performance over time. The main advantage of the bootstrap approach, as opposed to traditional parametric approaches is that it does not require the assumption of normality to be fulfilled, and by that give you a better understanding of mutual funds' performance in general. Following a null hypothesis of a zero α, a bootstrap procedure's main purpose in this scenario is to investigate if there exist too many excess returns in the left and/or right tail of the distribution.

Kosowski et al. (2006) find in their analysis that the average fund manager does not generate a high enough alpha to outperform the benchmark, net of fees. They explain that this could arise as managers with superior skill that perform better than the benchmark is outbalanced by the inferior managers that underperform. In explaining their choice of research model, and why they chose to use the bootstrap method, they show to the non-normality of the empirical distribution that is present in the residuals of most mutual funds, and how it could lead to a poorly distribution of alpha.

Kosowski et al. (2006) explains that this could arise as a result of several factors, where they firstly refer to that single stocks within most mutual fund portfolios tend to have kurtosis and skewness that make them not normally distributed, as well as how their returns tend to be auto-correlated. Consequently, the Central Limit Theorem would not apply if the sample size is not sufficiently large enough for it to be statistically significant, and that active fund managers who aim to maximize return on average are less diversified with larger positions in fewer stocks. Secondly, by not controlling for the heterogeneous risk-taking employed by different mutual fund managers, and the presence of higher moments in mutual fund alphas, Kosowski et al (2006) show that this may produce cross-sectional alpha distributions with thick, or thin tails that may lead to an over/ under-rejection of the null (in the absence of bootstrap). The statistical significance could therefore end up providing better results if a non-parametric method, such as the bootstrap method were to be utilized. In 2010 Fama and French provided an extension to the Kosowski et al. (2006) method by jointly sampling their residuals, both net and gross of fees, and thus gaining a significant advantage. They were then able to capture the correlated heteroskedasticity of mutual fund returns and the disturbances of the benchmark model. Motivated by their findings, we aim to perform a bootstrap simulation using the same methodology as both Kosowski et al. (2006) and Fama and French (2010), but our main focus will be on the latter as we also includes gross returns, and want to account for the possibility of correlation between return of factors and residuals.

The disadvantage of this method is that there will be some months where funds don't exist at all, as months are randomly sampled from the whole period.

We have therefore decided to focus on the t-statistic of alpha *($t(\alpha)$)* as opposed to α when interpreting the results. Both Kosowski et al. (2006) and Fama and French (2010) explain the $t(\alpha)$ superiority to only using α, with its power to control for the differences in precision, and the reliability of the estimated α when comparing funds. Given a distributional assumption, the $t(\alpha)$ will give us a more precise result than α, as α generates a higher variance in the distribution. The higher variance in the distribution will eventually lead to more spurious outliers in the cross-section of α, that consequently will provide more biased results. As $t(\alpha)$ is normalized by the standard deviation, Kosowski et al. (2006) explains that the heterogeneity in risk taking would not bring about nonnormalities by itself, and therefore act as a better test-statistic.

A disadvantage of both methods, and of bootstrapping in general is that random sampling of months in a simulation run would preserve the cross-correlation of returns, but lose all effects of autocorrelation (Fama and French 2010). Following in the section below is the bootstrap procedure that we implemented.

4.3.2 Bootstrap procedure

The first step in the bootstrap procedure[2] is according to Kosowski et al. (2006) to lay down a model for the factor returns in order to estimate α and the corresponding $t(\alpha)$ from each fund in the sample. Our factor model of choice for the bootstrap procedure is the Fama and French five-factor model (Eq.7). The general factor model in an OLS framework that we implemented can be illustrated by:

$$R_{i,t}^{e} = R_{i,t} - R_{f,t} = a_i + \sum_{j=i}^{K} \hat{\beta}_{i,j} \hat{f}_{j,t} + e_{i,t} \tag{10}$$

where the $R_{i,t}^{e}$ is the excess return for fund i at time t, found by taking the monthly return $R_{i,t}$ less the risk-free rate $R_{f,t}$. a_i is each fund's estimated α, and the $\hat{\beta}_{i,j}$ is estimated coefficients from the factor exposures $\hat{f}_{j,t}$, for K factors in the model.

[2] For a more detailed description of the bootstrap procedure, see Kosowski et al. (2006) and Fama and French (2010).

After running the regression in Eq. (10), all the estimated coefficients, α, $t(\alpha)$, and the residuals are saved for each fund i.

In the next step Fama and French (2010) implemented their modifications to the procedure by jointly sampling the residuals. A (T x 1) vector is drawn from the uniform distribution $U_t(0,1)$ of random data points from the 10,000 simulations, where T is the number of observations used in our sample of mutual funds. The (T x 1) vector is then multiplied by T. This process is then rounded up to the nearest integer that will generate the following (T x 1) vector:

$$\tilde{T}_s = round\ (Tx\ \{U_t(0,1)\}_{t=1}^{T}),\ s = 1, \ldots 10{,}000. \qquad (11)$$

The next step in the process is that for all the (T_s) of the factor returns estimated above are put into a (T x K) matrix, K being the number of factor returns. The same process is also done for the (T_s) of each funds residual that would generate a (T x N) matrix, where N is the number of mutual funds in the sample.

The next step is to construct a pseudo time series in excess of the risk-free rate that have jointly sampled factor returns and residuals, and by construction giving it the property of a zero true alpha by removing alpha from Eq. (10).

$$R_{i,t}^{e,s} = \sum_{j=1}^{K} \hat{\beta}_{i,j} f_{j,t}^{s} + \hat{\varepsilon}_{i,t}^{s} \qquad (12)$$

These pseudo returns are then ran on the original first - time factor model; Eq. (10) for each fund, keeping the random draw constant, and to obtain the newly simulated bootstrapped α and its corresponding $t(\alpha)$ for the S = 10 000 simulations. This generates a (1 x N) matrix of bootstrapped α. Following the inclusion rules of Fama and French (2010), then a fund that fail in delivering eight valid returns will not be included further in the bootstrap.

Finally, to be able to evaluate the results from the bootstrap procedure we compute the percentage of times that the actual α and the corresponding $t(\alpha)$ are larger than the simulated values from the five best, five worst and for funds at specific percentiles, ranging from the 10th percentile worst to the 90th percent best.

$$\%\ (Simulated < Actual)_{\alpha} = \frac{1}{S} \sum_{s=1}^{S} 1 \left[\alpha^{Simulated} < \alpha^{Actual}\right] \qquad (13)$$

$$\%\ (Simulated < Actual)_{t(\alpha)} = \frac{1}{S}\sum_{s=1}^{S} 1\left[t(\alpha)^{Simulated} < \ t(\alpha)^{Actual}\right] \qquad (14)$$

4.4 Regression assumptions

In order to obtain reliable and valid regression results, some regression assumptions need to be fulfilled. It is the two following issues that will be of most importance to our analysis.

1. *No autocorrelation of residuals.*

To test our sample for autocorrelation we used the Durbin Watson test, and the estimates are shown in Appendix 2. The test results indicate that 77 % of the sample is slightly negatively correlated, while the rest is slightly positively correlated. To correct for autocorrelation, we used the Newey West (1987) standard error correction.

2. *Homoscedasticity of residuals*

To test for heteroscedasticity, we used the Breusch - Pagan test, and the results are shown in Appendix 2. The null hypothesis of the test is that the data is homoscedastic. The results show that the null hypothesis was rejected for 8 % of the sample at a 5 % significance level, meaning that they are heteroscedastic. Again, we used the Newey West (1987) corrected standard errors which corrects for both autocorrelation and heteroscedasticity.

5.0 Data collection

5.1 Sample period and fund selection

The sample period that we use in this paper are monthly observations that ranges from January 2009 to December 2017. We decided that 2009 would be the best starting point as we would remove extreme outliers and financial side- effects that the subprime crisis in 2008 could impose on the results.

To figure out what funds to include within our fund categorization of Norwegian global funds, we used VFF. They provide yearly reports on all mutual fund activity in Norway. As of February 2018, there exists according to VFF; 102 global mutual funds in Norway. We are going to exclude those that fall into the passive management category, and those with less than 12 months of observations. This is because funds tend to adopt more risky strategies in its early stages of the life cycle. We ended up with 66 funds in our sample that were said to be actively managed, and that charged fees for active management. To extract the data needed for our analysis we used Thomson Reuters Eikon, available at BI Oslo. This is a platform that contains historical datasets of financial time series and cross-sectional statistics.

5.2 Survivorship Bias

Previous research on mutual fund performance and survivorship bias have shown to the importance of accounting for survivorship bias, where both surviving and non-surviving funds should be included in order to provide the most reliable results. Elton, Gruber and Blake (1996) shows that delisted funds are mostly categorized by the fact that they have performed very poorly over a time period, and thus if we decided to omit those funds there would be a high probability of ending up with an overestimation of average performance. To the extent that survivorship bias would affect our results by omitting delisted funds are illustrated in Figure 4 and 5. Here the cumulative returns of a portfolio consisting of only surviving funds provided superior returns in regard to a portfolio consisting of only delisted funds. Therefore, in order to account for survivorship bias in our dataset, we choose to include all funds that have existed for the whole sample period, been delisted during the sample period and lastly funds that was initiated after the start of our sample period. Kosowski et al. (2006) that performed a bootstrapping analysis as previously described, included only mutual funds that have existed for five years in their analysis, while Fama and French (2010) excluded funds that did not exist five years before the end of their sample period.

5.3 Monthly return

In calculating the monthly return for each fund, we used its historically reported net asset value (NAV) from Eikon. NAV is essentially the total book-value of a company's assets. It is calculated by taking the fund’s total assets and subtracting the value of intangible assets minus both short and long-term liabilities. NAV is gross of taxes but net of operating expenses. By using NAV, we are able to calculate the monthly net return that each fund provides. The calculation of net monthly return is illustrated in the formula below:

$$r_{i,t} = \frac{NAV_{i,t}}{NAV_{i,t-1}} - 1 \tag{15}$$

We then went on to calculate the gross return, as it is according to Morningstar useful in simulating the return that investors would have received if they had not paid any expenses. This comes from the assumption that fees are based on ending net assets.

$$EGR_i = \frac{(r_i+1)}{\left(1-\frac{ER_j}{12}\right)} - 1 \tag{16}$$

where EGR_i is the gross return for month i, r_i is the actual return for month i and ER_j is the expense ratio for the fiscal year that covers month i.

5.4 Expense Ratio

The fee charged by each fund in our sample is illustrated either by the operating fee stated at Morningstar, or at the respective funds latest available prospectus. The expense ratio of a mutual fund is according to Morningstar usually comprised of three components: management fees, administrative fees and advertising fees. The management fee is the fee that the fund manager takes to "actively" manage the fund on a daily basis, while the administrative fee is costs not included in the management fee, such as staffing costs and office rental cost. The last fee; Advertising fee, also known as 12b-1 is the cost associated with advertising the fund to potential investors.

To calculate gross returns, we will need to subtract the operating expenses from NAV since NAV is net of operating expenses. The major drawback with using mutual funds expense ratio in calculating gross returns is that it does not include trading costs. Trading costs vary over time and often with the activeness level of the fund. We were not able to obtain the trading costs, which in turn is unfortunate as our calculations of gross returns therefore is not gross of all expenses. Our tests on gross return will therefore be in line with the methodology of Fama and French (2010), in showing that a mutual fund only possess skills if estimates of α covers the trading costs missing from the expense ratio.

5.5 Risk free rate

Since there are no investment instruments that guarantees an absolute risk-free rate, we would need to establish a proxy for that purpose. Fama and French (2010), Carhart (1997) and Kosowski et al. (2006) all used the one-month Treasury bill as their proxy for risk free rate. We decided to use this as well, as all of our fund data is extracted in USD. From the Kenneth R. French Data Library, we obtained the one-month Treasury bill in USD. As our sample consists of Norwegian mutual funds that primarily invests in the global market, it entails that investors are exposed to various exchange rate risks between the domestic (NOK) currency and foreign currency. Some funds employ currency hedging as part of their investments strategy, while other funds take on more risk to generate higher returns.

5.6 Benchmark

The most commonly used benchmark for global mutual funds in Norway is according to Morningstar the MSCI World NR USD. We therefore find it to be the most appropriate benchmark for the whole sample. The MSCI World Index is a broad global equity benchmark that represents mid and large-cap performance across 23 developed markets countries (www.msci.com/world). In Appendix 6, all the member countries are listed for reference.

5.7 Summary statistics

Table 1: Summary of descriptive statistic of fund and benchmark returns.

The table shows the mean, standard deviation, minimum return, maximum return, skewness and kurtosis of the benchmark index and different equally- weighted fund returns. The benchmark index is the MSCI total return index for the world and the equally-weighted portfolios are; all funds that seized to exist during the full sample, funds that have been delisted during the sample and finally a portfolio of funds that are survivors during the whole sample. Panel A uses monthly returns net of fees, while Panel B uses monthly returns gross of fees.

Panel A: Entire sample 2009M01 - 2017M12 Net Returns

	Mean	Std.dev	Min	Max	Skewness	Kurtosis
MSCI	1,03 %	4,16 %	-10,24 %	11,22 %	-0,26	3,56
EW All Funds	0,95 %	4,46 %	-10,68 %	13,15 %	-0,10	3,72
EW Delisted	0,63 %	3,72 %	-10,80 %	11,88 %	-0,01	5,07
EW Alive	1,00 %	4,56 %	-10,82 %	13,40 %	-0,10	3,75

Panel B: Entire sample 2009M01 - 2017M12 Gross Returns

	Mean	Std.dev	Min	Max	Skewness	Kurtosis
MSCI	1,03 %	4,16 %	-10,24 %	11,22 %	-0,26	3,56
EW All Funds	1,07 %	4,56 %	-10,81 %	13,59 %	-0,09	3,72
EW Delisted	0,70 %	3,73 %	-10,69 %	12,01 %	0,02	5,03
EW Alive	1,10 %	4,57 %	-10,73 %	13,52 %	-0,10	3,75

The equally weighted portfolio (EW) of net returns within all fund categories (all funds, delisted and alive) have a lower mean return than the Benchmark (MSCI). However, when looking at gross returns, we see that all funds combined, and the portfolio of only alive funds generated a higher mean return than MSCI. By investigating the Max and Min values, this becomes clear as the deviation between the Max values of both fund categories and the MSCI is more significant than when comparing Min values. Another observation to point out is that the standard deviation of all EW portfolios (ex EW Delisted) is higher than the MSCI both net and gross, which in turn would imply that the variability in the returns is larger.

Table 2: Summary of descriptive statistics of Fama and French 5-factor returns.

The table shows the mean, standard deviation, minimum return, maximum return, skewness and the kurtosis of the global factors in Fama and French 5-factor model.

Panel A: Entire sample 2009M01 - 2017M12 Factor Returns

	Mean	Std.dev	Min	Max	Skewness	Kurtosis
Rm-Rf	1,02 %	4,16 %	-10,25 %	11,21 %	-0,26	3,57
SMB	0,15 %	1,34 %	-3,28 %	3,92 %	0,00	2,85
HML	-0,71 %	1,82 %	-4,60 %	4,86 %	0,37	3,10
RMW	0,27 %	1,17 %	-2,65 %	3,24 %	-0,04	2,69
CMA	-0,06 %	1,17 %	-4,03 %	2,87 %	-0,54	4,37

Table 3: Correlation matrix of global factor variables

The table shows the cross-correlation of the global four and five-factor models over the total time period.

	Rm-Rf	*SMB*	*HML*	*RMW*	*CMA*	*WML*
Rm-Rf	1,00					
SMB	-0,08	1,00				
HML	0,32	0,08	1,00			
RMW	-0,39	-0,33	-0,54	1,00		
CMA	-0,14	-0,06	0,44	-0,16	1,00	
WML	-0,39	-0,12	-0,38	0,28	0,34	1,00

6.0 Results and analysis

In this section we will present and discuss the empirical results. We will start by looking at fund activeness, evaluated using R^2 and tracking error. Following this, we will evaluate the fund performance by looking at the α estimates. This is done both net and gross of fees from individual fund regressions, as well as an equally weighted portfolio. Lastly, we will provide a comparison of the different results provided from the Kosowski et al. (2006) bootstrap procedure, and the modified procedure by Fama and French (2010).

6.1 Activeness of funds

6.1.1 R^2

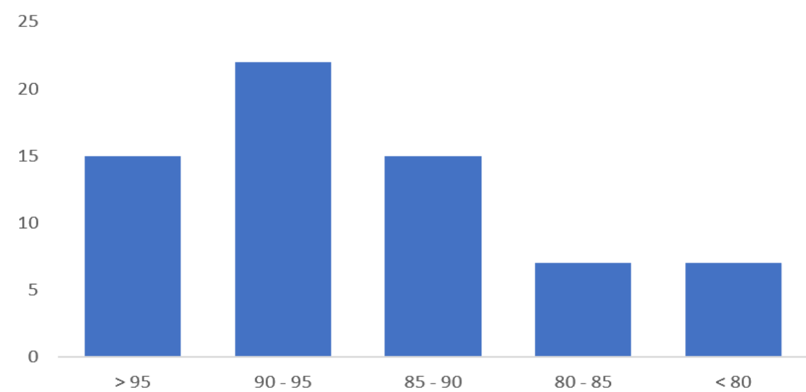
The rightmost column in table 5 shows the average R^2 obtained from individual regressions of each fund in our sample. When applying the three-factor model gross of fees the average R^2 is 0.8712. The average R^2 increases to 0.8824 when applying the five-factor model gross of fees. The median R^2 is 0.9119 and is represented by Holberg Global A. This means that the five-factor benchmark model explains 91.19 % or more of the variations in returns for half of the sample. This indicates that more than 50 % of our total sample of funds are either closet indexers or close to being closet indexers.

We find that the most active funds, KLP Framtid and Sektor Global Equity Kernel A NOK, are rather new and have only operated 12 and 24 months, with an R^2 of 0.2670 and 0.4707 respectively. The low R^2 may reflect an outlier-type strategy or estimation error due to few observations (Amihud & Goyenko, 2013).

As shown in Appendix 3, 15 of the funds have R^2 above 0.95 and can therefore be classified as closet indexers. This amounts to 22.73 % of the total sample. Another 22 funds have an R^2 somewhere between 0.90 and 0.95 and are therefore close to being classified as closet indexers. This is consistent with Petajisto (2013) who found that approximately one-third of all mutual funds were closet indexers, as well as Smørgrav & Næss (2011) who found that about 20 % of Norwegian mutual funds were closet indexers. Figure 3 below shows the R^2 distribution of the funds in our sample.

Figure 3: R^2 Distribution

The histogram shows the number of funds within different intervals of R^2. The leftmost post shows the number of funds with an R^2 higher than 95 percent, while the rightmost post shows those with an R^2 lower than 80 percent.



6.1.2 Tracking Error

When we look at the activeness of fund management using tracking error, the results are similar to the results from using R^2. 15 funds have a tracking error below 4 % and can hence be classified as closet indexers. This is the same amount that we found using R^2. This indicates that tracking error and R^2 yields similar ranking in terms of active management. Table 4 further supports this. The table shows the 10 most active and the 10 least active funds, ranked by both measures. When looking at the least active funds, the same 10 funds appears on both rankings. Out of the 10 most active funds, 8 of them appears on both rankings. KLP Framtid, which is the most active fund in terms of R^2, does not appear on the tracking error top list. This is supported by Amihud & Goyenko (2013) who suggests that it could be due to estimation error.

Table 4: Fund activeness

The table shows the 10 most active and the 10 least active funds ranked by R^2 and tracking error.

Most Active

Ranking	Fund Name	R^2	Fund Name	Tracking Error
1	KLP Framtid	0,2670	ODIN FORVALTNING AS GLB. SMB N	12,25 %
2	Sector Global Equity Kernel A NOK	0,4707	Arctic Global Equities H	10,06 %
3	Sector Global Equity Kernel P NOK	0,6135	FRAM Global Open Fund	9,81 %
4	ODIN GLOBAL II	0,6210	Danica Pensjon Norge - Aksjer	9,64 %
5	KLP AksjeGlobal Lavbeta II	0,6487	Sector Global Equity Kernel P NOK	9,39 %
6	Arctic Global Equities H	0,6705	DNB AM Global Valutasikret	9,32 %
7	FRAM Global Open Fund	0,7649	KLP AksjeGlobal Lavbeta II	8,84 %
8	DNB AM Global Valutasikret	0,8052	Sector Global Equity Kernel A NOK	8,78 %
9	SKAGEN Focus A NOK	0,8211	SKAGEN Focus A NOK	8,24 %
10	Nordea 1 - Global Value BP NOK	0,8251	Nordea 1 - Global Value BP NOK	7,34 %

Least Active

Ranking	Fund Name	R^2	Fund Name	Tracking Error
57	DNB Global (IV)	0,9726	DNB Global (IV)	2,95 %
58	Landkreditt Aksje Global Open Fund	0,9729	DNB Global (I)	2,91 %
59	DNB Global (III)	0,9732	DNB GLOBALSPAR	2,89 %
60	DNB Global (I)	0,9734	DNB Global (III)	2,88 %
61	DNB GLOBAL II	0,9802	DNB GLOBAL ETISK IV	2,80 %
62	Storebrand Global Multifaktor	0,9809	DNB GLOBAL V	2,67 %
63	DNB GLOBAL ETISK IV	0,9830	DNB GLOBAL II	2,65 %
64	DNB GLOBAL SELEKTIV I	0,9844	DNB GLOBAL SELEKTIV I	2,64 %
65	DNB GLOBAL V	0,9857	Landkreditt Aksje Global Open Fund	2,49 %
66	DNB GLOBALSPAR	0,9861	Storebrand Global Multifaktor	2,31 %

6.2 Performance

6.2.1 Equally weighted portfolio regression results

To obtain a fair overview of the overall performance of Norwegian global mutual funds, we generated an equally-weighted portfolio, consisting of the excess return of all the funds in our sample. We used the portfolios excess return as the dependent variable against factors from the three, four and five-factor models. The results can be seen in table 5 below, shown for both net and gross monthly returns.

Table 5: Fund performance

The table shows the different factor loadings obtained from the time-series regression of an equally weighted portfolio. Each coefficients t-statistic is stated in parentheses and is corrected using the Newey and West (1987) procedure. An equal-weighted portfolio is compared to the Fama-French 3 and 5 factor models and the Carhart 4-factor model throughout the whole sample from 2009-2017. Average R^2 is obtained from individual fund regressions. Results are shown both net and gross of operational fees.

Model		α	mkt-rf	SMB	HML	WML	RMW	CMA	R^2	Adj R^2	Average R^2
Fama & French 3- factor model	*Net of fees*	-0,0019	1,0965	0,1774	-0,0655				0,9759	0,9752	**(0,8712)**
		(-2,60)	(61,9)	(-3,48)	(-1,62)						
	Gross of fees	-0,0009	1,0976	0,1776	-0,0658				0,9759	0,9752	**(0,8712)**
		(-1,20)	(61,91)	(-3,48)	(-1,63)						
Carhart 4- factor model	*Net of fees*	-0,0017	1,0816	0,1602	-0,0982	-0,0555			0,9774	0,9763	**(0,8792)**
		(-2,36)	(59,63)	(3,2)	(-2,38)	(-2,62)					
	Gross of fees	-0,0006	1,0828	0,1603	-0,0985	-0,0554			0,9774	0,9763	**(0,8791)**
		(-0,93)	(59,63)	(3,20)	(-2,39)	(-2,62)					
Fama & French 5- factor model	*Net of fees*	-0,0022	1,0898	0,1898	0,0006		0,0962	-0,1635	0,9775	0,9765	**(0,8784)**
		(-2,84)	(55,55)	(3,34)	(0,01)		(1,24)	(-2,35)			
	Gross of fees	-0,0012	1,0909	0,1874	0,0003		0,0963	-0,1636	0,9775	0,9765	**(0,8824)**
		(-1,51)	(55,56)	(3,34)	(0,01)		(1,24)	(-2,35)			

The differences in adjusted R^2 are very small among the different models, but the five-factor model has the highest adjusted R^2 of 0.9765. This indicate that the five-factor model is superior to the three- and four-factor models as it captures the variation in returns to a slightly weak, but still greater extent. We observe that all the factor models exhibit negative and non-significant *α,* gross of fees. When looking at monthly returns net of fees, the three- and four-factor models exhibit negative *α*, but significant at the 5 % level. The five-factor model exhibit a negative *α*, significant at the 1 % level. The *α* of the equally weighted portfolio, net of fees is - 0.22 % per month using the five-factor model. This *α* estimate is 2.84 standard deviations below zero and therefore provides strong evidence that the returns of the portfolio of all global funds are below the returns provided by the factor model. When adding back fees, the five - factor model *α,* gross of fees has increased to -0.12 % per month. The *α* estimate is now 1.51 standard deviations below zero, which in turn would indicate that even after the fees are subtracted from the returns, the average global mutual fund manager is not able to provide abnormal returns for the investors. Overall, these results provide support to a hypothesis that on average, Norwegian global mutual funds are not able to beat their respective benchmark before or after fees.

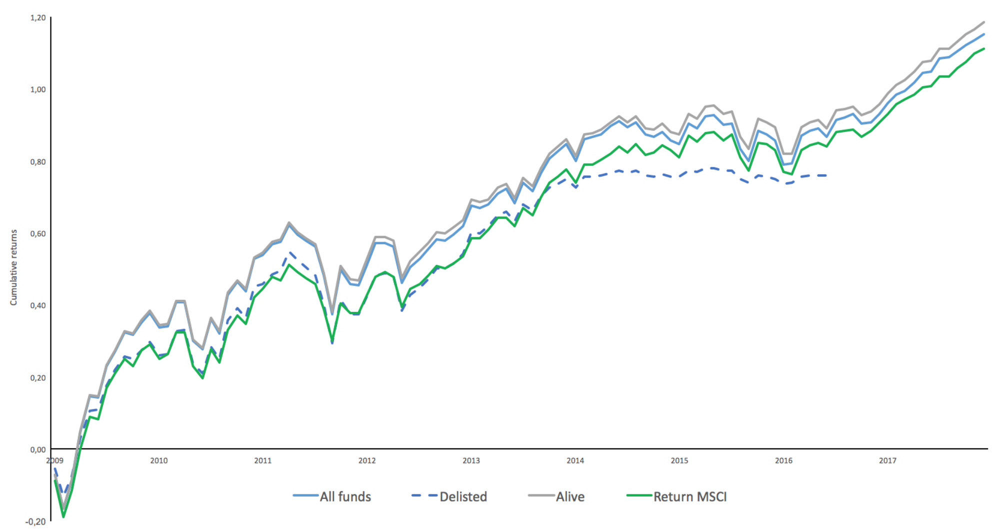
We further observe significant market coefficients above 1, suggesting heavy loading and exposure to the market portfolio. The equal weighted portfolio has a positive and significant exposure to the SMB factor for all the factor models, indicating that the funds are more exposed to the average return of small companies (size). The exposure to the HML factor is negative and statistically significant for the three- and four-factor models, but becomes positive and non-significant when moving to the five-factor model. The four-factor model exhibit a negative and statistically significant exposure towards the WML factor, while the five-factor model shows a positive, but non-significant exposure towards the RMW factor, and a significant negative exposure towards the CMA factor.

Figure 4: Cumulative net fund performance

The graph shows the equal weighted returns on all funds, delisted funds, surviving funds and the MSCI benchmark index net of fees in the period 2009 to 2017.

Figure 5: Cumulative gross fund performance

The graph shows the equal- weighted returns on all funds, delisted funds, surviving funds and the MSCI benchmark index gross of fees in the period 2009 to 2017.



When comparing the performance returns in terms of costs, we see from figure 4 that the equally weighted portfolio over the past five years on average provided returns lower than of the benchmark index net of fees, as opposed to the time period of 2009-2014. This is interesting, as figure 5 illustrates that gross of fees the portfolio has overperformed the benchmark at every point in time during the entirety of the sample period. This would therefore imply from a specifically observational perspective, that from 2014 and forward, fund managers have not been able to provide superior returns in regard to its benchmark for its investors after costs. One should on the other hand refrain from drawing conclusions from this result, as an equally- weighted portfolio could impose misleading results. It could also have been interesting to look at an value-weighted portfolio, but this turned out to be difficult as we wanted a dataset free of survivorship bias. This is because delisted funds for obvious reasons do not provide assets under management, so including them in a value-weighted portfolio would provide misleading results.

6.2.2 Individual fund regression results

The table in appendix 4 presents the results from regressions of monthly return net of fees, while the table in appendix 5 presents the results from regressions of monthly return gross of fees, both using the five-factor model. The tables show the top 10 performing funds, the bottom 10 performing funds as well as the median fund ranked by the alpha's t-statistic.

Using gross returns, we see that all of the top 10 funds deliver a positive α. However, only the two best funds are statistically significant at the 10 % level. The two best funds are Storebrand Global Multifaktor and Storebrand Global Verdi and they provided a monthly α of 0.13 % and 0.22 % respectively. The 10 worst performing funds all delivers significant negative α, the nine worst statistically significant at the 5 % level, and the four worst even significant at the 1 % level. We also observe that out of the top 10 funds, nine of them have a R^2 above 0.90 and six of them above 0.95. Looking at the worst 10, only one fund has a R^2 above 0.95. This supports a passive investment strategy, and suggest that the more you deviate from the index, the more you lose. This is not in line with Petajisto (2013) who found that the most active stock pickers outperformed their benchmark indices even after fees, while closet indexers underperformed. Using net returns, we see that all of the top 10 funds still delivers positive α, but all of the α are now non-significant. All of the 10 worst performing funds delivers negative α statistically significant at the 5 % level, and seven of them even significant at the 1 % level. The median fund is represented by Skagen Global II NOK and it has delivered a monthly α of -0.19 %. The results support many of the previous studies done, e.g. Malkiel (1995), Sørensen (2009) and Cumby and Glen (1990) in showing to actively managed funds being unable to deliver alpha net of fees. Our findings are therefore also in line with Sharpe (1991) who stated that the index net of cost will always outperform an actively managed dollar, which suggest that the market is somewhat efficient.

Only three of the top 10 funds have existed the whole sample period, which means seven of them have fewer observations. KLP Framtid which is the fifth best have for instance only 12 months of observations. Kosowski et al. (2006) shows to the fact that short-lived funds' cross-section α may be inflated due to the fact that they are more subject to survivorship bias and a higher dispersion than funds with longer longevity. Short-lived funds are often smaller funds and may therefore impose a more risk-taking strategy in its early life in order to gain a competitive edge. Liang, B (1999) provides an explanation to the over-performance seen by younger funds with that these managers are working harder in building the funds' reputation that is required to attract capital from outside investors.

We also observe some differences in the exposure to the different risk factors between the best and worst performing funds. We find that the bottom 10 funds are more exposed to the market portfolio and average return of small companies than the top 10 performing funds.

Overall, the results from the individual fund regressions show weak evidence of abnormal fund performance. It suggests that some skilled managers are able to beat their benchmark index before fees, but the trade-off between good performers and bad performers is outweighed by the latter. This is investigated further in section 6.3.

6.3 Bootstrap results

In this section we will present our findings from the application of the Kosowski et al. (2006) bootstrap procedure, as well as the modified procedure of Fama and French (2010), utilizing the Fama and French (2014) five-factor model. Table 6 reports the results using net returns, while Table 7 reports the results using gross returns. In both tables, the second and fifth column in each panel ("simulated") shows the bootstrapped α-value and $t(\alpha)$ respectively, ranked from worst to best, while the third and sixth column ("Actual") shows the simulations associated "actual" values. The "actual" values used are the results from the individual fund regressions reported in Appendix 4 and 5. Finally, the fourth and seventh row ("% < Actual") in each panel respectively reports the percentage of times that the actual value exceeds the associated simulated value generated from the two different bootstrap procedures.

Table 6: Bootstrap results using net returns

The table shows the actual and the simulated α and the $t(\alpha)$ from both the Kosowski et al. (2006) bootstrap procedure and the Fama-French (2010) modified procedure. Panel A and B shows the Kosowski et al (2006) and Fama-French (2010) methods respectively, net of fees. The leftmost column in each panel ranks each fund in respect to both α and $t(\alpha)$, while the rightmost column lists the percentage in which the actual α and $t(\alpha)$ were larger than the bootstrap generated coefficients.

Panel A: Kosowski et al. Method net returns

	Alpha			t (alpha)		
Rank	**Simulated**	**Actual**	**% < Actual**	**Simulated**	**Actual**	**% < Actual**
5-factor Net Returns						
Worst	0,00001	-0,01161	0,00 %	0,00622	-6,36371	0,00 %
2nd	0,00000	-0,00873	0,00 %	0,01090	-5,73097	0,00 %
3rd	0,00001	-0,00798	0,00 %	0,01566	-5,51311	0,01 %
4th	0,00002	-0,00645	0,59 %	-0,06744	-3,68341	0,08 %
5th	0,00001	-0,00644	0,00 %	-0,03349	-3,44851	0,22 %
10 %	0,00000	-0,00611	0,00 %	0,01369	-3,05407	0,21 %
20 %	-0,00002	-0,00501	0,06 %	-0,02024	-2,38443	1,56 %
30 %	-0,00002	-0,00328	0,66 %	-0,04386	-1,76845	5,67 %
40 %	-0,00001	-0,00263	2,54 %	-0,05109	-1,46976	9,28 %
50 %	-0,00001	-0,00213	7,63 %	0,02181	-1,24069	11,42 %
60 %	0,00000	-0,00156	34,04 %	-0,03088	-1,10101	16,38 %
70 %	0,00001	-0,00120	26,67 %	0,01027	-0,94755	18,20 %
80 %	-0,00001	-0,00039	39,44 %	0,01512	-0,30413	38,80 %
90 %	-0,00001	0,00042	65,92 %	-0,00632	0,27701	60,93 %
5th	0,00000	0,00070	75,47 %	0,01331	0,46251	67,06 %
4th	0,00000	0,00075	76,93 %	-0,03975	0,48279	67,54 %
3rd	-0,00001	0,00080	64,95 %	-0,00129	0,50311	68,22 %
2nd	-0,00004	0,00090	59,15 %	-0,06452	0,59568	71,98 %
Best	0,00001	0,00157	77,20 %	0,04383	1,23099	85,95 %

Panel B: Fama and French Method net returns

	Alpha			t (alpha)		
Rank	**Simulated**	**Actual**	**% < Actual**	**Simulated**	**Actual**	**% < Actual**
5-factor Net Returns						
Worst	0,00000	-0,01161	0,00 %	0,00647	-6,36371	0,00 %
2nd	0,00000	-0,00873	0,00 %	0,00339	-5,73097	0,00 %
3rd	0,00001	-0,00798	0,00 %	0,01568	-5,51311	0,00 %
4th	0,00001	-0,00645	0,00 %	-0,02968	-3,68341	0,00 %
5th	0,00001	-0,00644	0,00 %	-0,01254	-3,44851	0,00 %
10 %	0,00000	-0,00616	0,00 %	-0,00219	-3,30321	0,00 %
20 %	0,00000	-0,00611	0,00 %	-0,00007	-3,05407	0,00 %
30 %	0,00000	-0,00505	0,15 %	0,01352	-2,42019	0,00 %
40 %	0,00001	-0,00329	0,03 %	0,00591	-1,78735	0,17 %
50 %	0,00001	-0,00263	0,06 %	-0,01274	-1,46976	1,13 %
60 %	0,01259	-0,00213	1,33 %	2,04966	-1,24069	0,10 %
70 %	0,01516	-0,00156	3,75 %	1,75745	-1,10101	0,37 %
80 %	0,01020	-0,00114	8,02 %	1,53630	-0,94392	1,83 %
90 %	0,00002	-0,00025	41,17 %	-0,01516	-0,22357	32,88 %
5th	0,00000	0,00042	78,09 %	-0,00322	0,27701	68,78 %
4th	0,00000	0,00049	81,25 %	-0,00727	0,31820	69,76 %
3rd	0,00000	0,00070	89,15 %	-0,00307	0,46251	77,43 %
2nd	0,00000	0,00075	90,87 %	-0,01773	0,48279	79,12 %
Best	-0,00001	0,00157	91,70 %	0,00728	1,23099	95,90 %

In Table 6 using net returns, we see that in general the likelihood of the ability of skill to cover costs are scarce. Taking both the Kosowski et al. (2006) model in Panel A and the Fama and French (2010) model in Panel B to consideration, the overall consensus is that only the top 10 % of fund managers have more than 50 % of its actual five-factor $t(\alpha)$ higher than those generated from the 10,000 simulation runs. In perspective, these are also about the only funds that provide positive $t(\alpha)$. For example, at the 70th percentile in Panel A, the cross-section of the $t(\alpha)$ is -0.95, where only 18.20 % of the actual values are better than the simulations using the Kosowski et al. (2006) procedure. Looking at the same percentile in Panel B from the Fama & French (2010) procedure, this number have decreased to 0.37 %. From the Fama and French (2010) method, the disconcerting fact is that funds ranking from the worst and all up to the 80th percentile, the actual values are lower than the simulation values in 98 % of the runs. This is an indication that the bad results cannot be explained by bad luck alone, but that inferior fund managers are destroying value. The takeaway from both models is that a greater part of mutual fund managers are not able to produce a high enough α to cover costs, net of fees. However, when looking at the most extreme right tails, we see that the cross-section of the actual *t(α)* on average is higher than from the simulations in both models. This occurs between the 80th and the 90th percentile with the Kosowski et al. (2006) method and at the fifth best fund using the Fama and French (2010) method. Our results using net returns are therefore to some degree similar to the findings of Fama and French (2010), where we can show to evidence in the extreme right tail that explains sufficient skill to cover costs that is not only due to luck.

Table 7: Bootstrap results using gross returns

The table shows the actual and the simulated α and the *t(α)* from both the Kosowski et al. (2006) bootstrap procedure and the Fama-French (2010) modified procedure. Panel A and B shows the Kosowski et al. (2006) and Fama-French (2010) method respectively, gross of fees. The leftmost column in each panel ranks each fund in respect to both α and *t(α)*, while the rightmost column lists the percentage in which the actual α and *t(α)* were larger than the bootstrap generated coefficients.

Panel A: Kosowski et al. Method gross returns

	Alpha			t (alpha)		
Rank	**Simulated**	**Actual**	**% < Actual**	**Simulated**	**Actual**	**% < Actual**
5-Factor Gross Returns						
Worst	-0,00001	-0,01017	0,00 %	-0,01455	-4,92394	0,00 %
2nd	-0,00002	-0,00848	0,00 %	-0,01082	-4,90427	0,00 %
3rd	-0,00001	-0,00757	0,00 %	-0,00076	-4,88179	0,00 %
4th	0,00000	-0,00619	0,09 %	0,01082	-2,93637	0,29 %
5th	-0,00003	-0,00500	2,87 %	-0,08361	-2,77419	1,21 %
10 %	0,00001	-0,00492	0,04 %	0,00902	-2,32455	1,73 %
20 %	0,00005	-0,00368	9,51 %	0,02699	-1,74733	4,73 %
30 %	0,00001	-0,00245	6,01 %	-0,00644	-0,96146	18,42 %
40 %	0,00001	-0,00148	8,94 %	-0,01280	-0,84589	21,43 %
50 %	-0,00001	-0,00097	25,40 %	0,02041	-0,72977	23,73 %
60 %	0,00000	-0,00065	21,62 %	0,03101	-0,50389	31,21 %
70 %	-0,00001	-0,00023	45,42 %	-0,00111	-0,09130	46,55 %
80 %	-0,00001	0,00047	61,78 %	-0,01741	0,32283	62,19 %
90 %	0,00000	0,00121	91,82 %	0,01260	0,78470	77,31 %
5th	-0,00001	0,00130	89,56 %	-0,00079	0,95175	81,27 %
4th	0,00001	0,00132	90,24 %	0,02852	0,95984	80,95 %
3rd	0,00000	0,00159	93,88 %	-0,04326	0,99527	83,22 %
2nd	0,00001	0,00201	82,95 %	0,00754	1,64143	93,47 %
Best	0,00005	0,00219	69,19 %	-0,03610	1,83042	95,73 %

Panel B: Fama and French Method gross returns

	Alpha			t (alpha)		
Rank	**Simulated**	**Actual**	**% < Actual**	**Simulated**	**Actual**	**% < Actual**
5-Factor Gross Returns						
Worst	0,00001	-0,01017	0,00 %	0,02414	-4,92394	0,00 %
2nd	0,00001	-0,00848	0,00 %	0,01649	-4,90427	0,00 %
3rd	0,00002	-0,00757	0,00 %	0,01512	-4,88179	0,00 %
4th	0,00000	-0,00619	0,00 %	0,01114	-2,93637	0,00 %
5th	-0,00001	-0,00500	0,07 %	-0,03764	-2,77419	0,01 %
10 %	0,00000	-0,00492	0,00 %	-0,00007	-2,32455	0,04 %
20 %	0,00001	-0,00368	0,94 %	0,01562	-1,74733	0,12 %
30 %	-0,00001	-0,00245	0,33 %	-0,00052	-0,96146	3,94 %
40 %	0,00000	-0,00139	2,84 %	-0,02123	-0,82238	8,10 %
50 %	0,00000	-0,00104	5,64 %	0,00441	-0,73247	9,19 %
60 %	0,01049	-0,00065	3,33 %	1,94970	-0,50389	1,33 %
70 %	0,01357	-0,00032	6,33 %	1,74872	-0,15311	5,16 %
80 %	0,01530	0,00013	11,84 %	1,42020	0,15658	14,64 %
90 %	0,00001	0,00091	74,81 %	0,00861	0,64306	84,55 %
5th	0,00001	0,00125	97,94 %	0,00543	0,85733	92,28 %
4th	0,00001	0,00130	98,23 %	0,00480	0,95175	92,15 %
3rd	0,00001	0,00132	98,22 %	0,00548	0,95984	92,94 %
2nd	0,00001	0,00159	99,35 %	-0,00343	0,99527	93,98 %
Best	0,00003	0,00219	81,92 %	-0,00230	1,83042	99,52 %

Table 7 above that shows results from the bootstraps using gross returns, illustrate to a better ability in using skills to cover costs. This is because the bootstrap procedure now work in a manner that shows the ability that managers have in order to cover the costs missing from the expense ratio (Fama and French, 2010). Overall the likelihood of the cross-section of the actual *t(α)* being higher than the simulations is better when employing gross returns in opposition to using net returns, as it also should be. However, almost all funds at the bottom spectrum still does not provide sufficient skills to cover costs. From the Fama and French (2010) method in Panel B we see a severe increase in the *t(α)* estimates from the 80th to the 90th percentile. Here the actual gross returns that beat the simulation runs leaps from 14.64 % to 84.55%, and the remaining top five funds all beat their simulation runs more than 90 % of the times. Conversely, looking at the Kosowski et al. (2006) method in panel A, we see a considerably more moderate increase when moving upwards from the 30th percentile. Here the top five funds beat the simulations more than at least 80 % of the times. This is lower than with the Fama and French (2010) method, but still high enough to suggest that both models enables us in using gross returns to reject the null hypothesis that managerial skill is due to luck only.

Figure 6: Kosowski et al. Bootstrap Kernel Density Estimate function

This figure illustrates the *t(α)* in a Kernel Smoothing Density Function from the bootstrap procedure of Kosowski et al. (2006). The left panel uses net returns while the right panels uses gross returns. Both models are based on the five-factor model (Equation 1). The t-statistic values used in the left panel (right panel) corresponds to the percentage of times that the actual values were greater than the simulated values, as illustrated in panel A in table 6 (table 7).

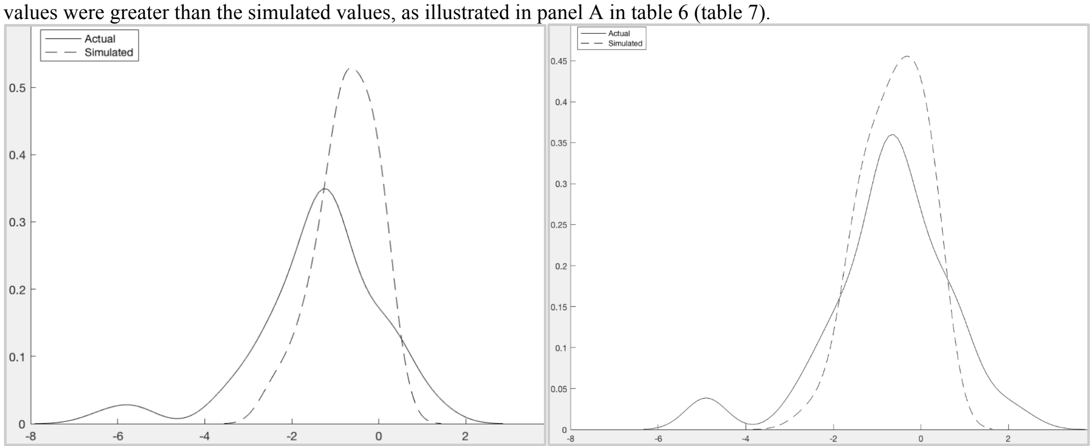


Figure 7: Fama & French Bootstrap Kernel Density Estimate function

This figure illustrates the actual and the simulated *t(α)* in a Kernel Smoothing Density Function from the modified bootstrap procedure of Fama and French (2010). The left panel uses net returns while the right panels uses gross returns. Both models are based on the five-factor model (Equation 1). The t-statistic values used in the left panel (right panel) corresponds to the percentage of times that the actual values were greater than the simulated values, as illustrated in panel B in table 6 (table 7).

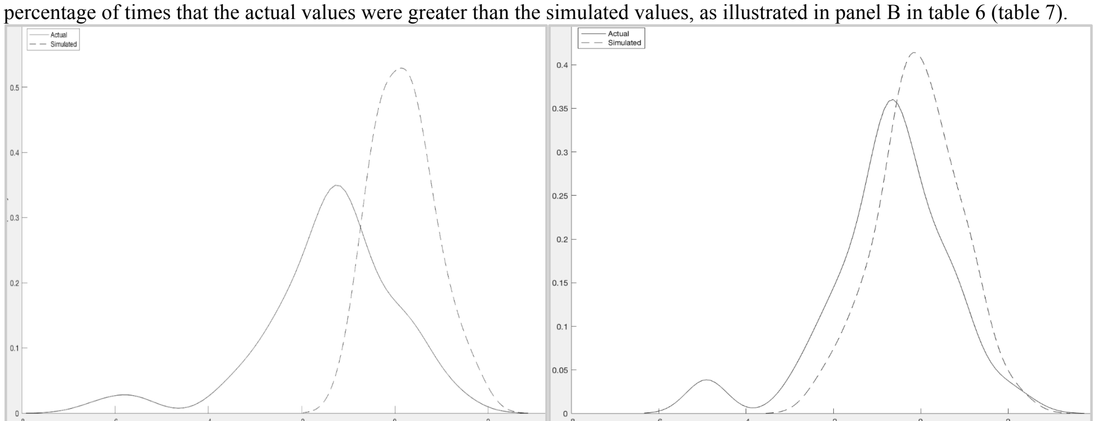


Figure 6 and 7 shows the Kernel density function as previously utilized by Cuthbertson, Nitzsche and O'Sullivan (2008), as an alternative interpretation of the bootstrap results. They implemented this method as a tool to identify how many funds that are expected to generate a given level of α by luck alone, and to compare this with the number of funds that actually achieved that level of α. The null hypothesis of the Kernel density estimations of the distribution of the actual and the bootstrapped $t(\alpha)$ entail zero outperformance, i.e. that it would lie within the *"Luck distribution"*.

Figure 6 that utilize the Kosowski et al. (2006) procedure shows that net of fees the left tail of the actual value distribution lies mostly to the left of the bootstrapped distribution, which according to Cuthbertson, Nitzsche and O'Sullivan (2008) would entail that the poor performance is due to bad skill as opposed to bad luck alone. Diversely, we find the right tail of the actual values to lie outside the luck distribution of the bootstrap, which in turn would signal the presence of outperforming funds. Looking at the rightmost graph in Figure 6, we see that gross of fees, the average of the actual distribution of $t(\alpha)$ have moved further into the center of the luck distribution, though the tails of the actual distribution still employ more or less the same properties as we saw net of fees.

Figure 7 from the Fama and French (2010) modified procedure shows that both gross and net of fees, the 'actual' distribution lies more to the left of the simulations. This arise as a result of that the luck distribution has shifted to the right, becoming more normally distributed around a zero α. This makes the left tail to contain more values (underperformers) and the right tail to have less values (overperformers) outside the luck distribution compared to the Kosowski et al. (2006) method. This could arise as a result of that the Fama and French (2010) procedure is more flexible in terms of the number of observations that are required (8 months) as opposed to the inclusion rule of 60 months in the Kosowski et al. (2006) method. This would according to Fama and French (2010) provide their method with less survivorship bias, since fewer delisted funds would be included and therefore provide a less extreme right tail in the distribution than the Kosowski et al. (2006) method.

Figure 8: Cumulative Density Function

This figure illustrates the cumulative density distribution of the actual vs. the simulated *t(α)*. The left panel shows the actual and the simulated cumulative density functions for the *t(α)* generated from the five-factor model net of fees, while the right panel shows the same, but gross of fees. The red lines represent actual values, whilst the blue line represents simulated values from the Fama and French (2010) modified bootstrap procedure.

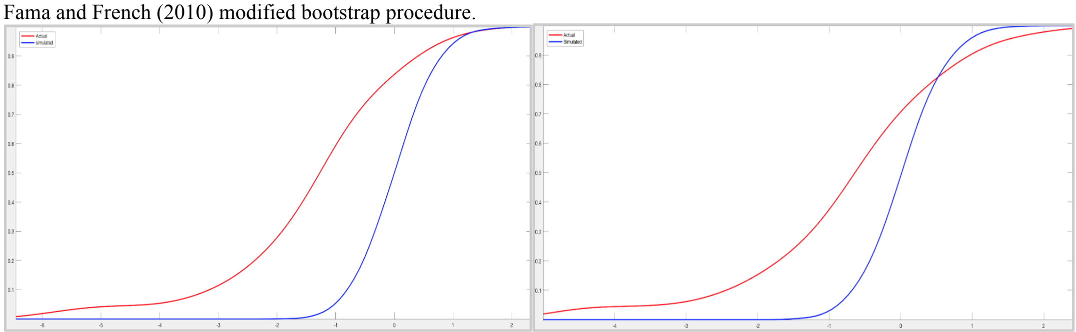


Figure 8 shows the actual and the simulated values of *t(α)* from the Fama and French (2010) bootstrap procedure in a cumulative distribution function. The leftmost panel shows the cumulative distribution function for five-factor returns net of cost. An investigation of the function shows that in the left-tailed distribution of the *t(α)*, all the actual net returns are worse than the simulated values from the bootstrap. When investigating the US mutual fund market, Fama and French (2010) provide similar results, where they predict that the inferior performance possibly arise as a result of that net returns are absorbed by expenses. In the right tail of our distribution we see the same as in the left tail, although when moving up to the 95th percentile and above, some of the actual and simulated values are close to equal on average. Taking this into consideration one could partly provide evidence that there actually exists some managers that provide a positive true *α* net of fees in regard to the passive benchmark. These results are also consistent with the results that we saw from Table 6 previously.

Our findings also possess similar characteristics to those of Fama and French's (2010) US fund market study, when we take the fees out of the equation and use gross returns. The rightmost panel in figure 8 shows that gross of fees, the left tail of the distribution provides evidence that there exist inferior fund managers that impose a negative true *α* in regard to the MSCI benchmark, i.e. the same result that net returns provided. However, when looking at the right tail of the distribution for gross returns it provides the opposite results to the left tail in favor of active management. This occurs from approximately the 85th percentile and above, where the actual values on average are better than the simulated. This would therefore imply that there exist some superior managers that provide a positive true α in regard to the benchmark.

7.0 Conclusion

Using R^2 and tracking error, we find that 22.73 % of Norwegian Global mutual funds who charge fees for active management can be classified as closet indexers, due to a R^2 above 0.95 and tracking error below 4 %. Another 33.33 % are close to being closet indexers.

The equally-weighted portfolio regression results suggest that on average, Norwegian global mutual funds are not able to beat their benchmark, both gross of fees and net of fees. The individual fund regression results suggest the same, but shows that some managers are able to beat their benchmark gross of fees. Our findings are in line with Malkiel (1995) and Sørensen (2009) who found little to no evidence of any abnormal performance of actively managed funds in respect to benchmark returns. The results differ from Petajisto (2013) who found that the most active stock pickers outperformed their benchmark indices even after fees, while the closet indexers underperformed.

When we conducted the bootstrap procedure of Kosowski et al. (2006) and the modified version as proposed by Fama and French (2010), we found what seems to be the consensus amongst previous research, namely that the average mutual fund investor does not possess enough skill to generate abnormal risk-adjusted returns both net and gross of fees. Our results investigating Norwegian based global funds are also fairly consistent with the findings of Fama and French (2010) that investigates the US fund market, in showing to strong evidence of some fund managers among the top quintile that bear the skills to deliver alpha, as well as strong evidence of underperformance in the left-tail of the distribution.

For further research one could investigate the same fund categorization as us, but implement a longer sample that includes the subprime crisis, in order to see if the results would hold during a recession as well. It would also be interesting to dig deeper into active management, using the fairly new measurement called Active Share to do a more thorough analysis of the activeness of Norwegian Global mutual funds.

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9.0 Appendix

Appendix 1:

List of all the funds included in the sample, in alphabetical order. * are funds initiated after 2009M01 and ** are funds delisted before 20017M12

Fund Name	Date Span	Observations
Alfred Berg Global Quant Open Fund	2009M01 - 2017M12	108
Arctic Global Equities A *	2011M01 - 2017M12	84
Arctic Global Equities B *	2011M01 - 2017M12	84
Arctic Global Equities H *	2015M06 - 2017M12	31
Arctic Global Equities I *	2010M12 - 2017M12	85
C WorldWide Globale Aksjer	2009M01 - 2017M12	108
C WorldWide Globale Aksjer Etisk	2009M01 - 2017M12	108
C WorldWide Stabile Aksjer	2009M01 - 2017M12	108
CARNEGIE WORLD WIDE ETISK II **	2009M10 - 2014M11	62
Danica Pensjon Norge - Aksjer	2009M01 - 2017M12	108
Danske Invest Investeringsprofil Aksjer Open Fund	2009M01 - 2017M12	108
Delphi Global Open Fund	2009M01 - 2017M12	108
DNB AM Global Valutasikret *	2014M02 - 2017M12	47
DNB Fund Global Value & Momentum **	2009M05 - 2016M02	82
DNB Global (I)	2009M01 - 2017M12	108
DNB Global (III)	2009M01 - 2017M12	108
DNB Global (IV)	2009M01 - 2017M12	108
DNB Global Etisk (V)	2009M01 - 2017M12	108
DNB GLOBAL ETISK IV **	2009M01 - 2014M02	62
DNB GLOBAL II **	2009M01 - 2015M08	80
DNB GLOBAL SELEKTIV I **	2009M01 - 2013M09	57
DNB GLOBAL V **	2009M01 - 2013M07	55
DNB GLOBALSPAR **	2009M01 - 2013M09	57
Eika Global	2009M01 - 2017M12	108
Forte Global *	2011M03 - 2017M12	81
FRAM Global Open Fund	2009M01 - 2017M12	108
Handelsbanken Global Tema (A1 NOK) *	2015M06 - 2017M12	31
Holberg Global A	2009M01 - 2017M12	108
HOLBERG GLOBAL B	2009M01 - 2017M12	108
KLP AksjeGlobal Lavbeta I *	2014M01 - 2017M12	48
KLP AksjeGlobal Lavbeta II *	2014M04 - 2017M12	45
KLP Framtid *	2017M01 - 2017M12	12
Landkreditt Aksje Global Open Fund	2009M01 - 2017M12	108
Nordea 1 - Global Value BP NOK **	2009M01 - 2016M05	89
Nordea Global NOK	2009M01 - 2017M12	108
NORDEA INTERNASJONALE AKSJER	2009M01 - 2017M12	108
NORDEA INTERNASJONALE AKSJER II	2009M01 - 2017M12	108
NORDEA INTERNASJONALE AKSJER III	2009M01 - 2017M12	108
Nordea Plan 100	2009M01 - 2017M12	108
Nordea Stabile Aksjer Global Etisk	2009M01 - 2017M12	108
ODIN FORVALTNING AS GLB. SMB NOK **	2009M01 - 2013M01	49
ODIN Global	2009M01 - 2017M12	108
ODIN Global A *	2015M07 - 2017M12	30
ODIN Global B *	2015M07 - 2017M12	30
ODIN Global D *	2015M07 - 2017M12	30
ODIN GLOBAL II **	2010M09 - 2016M04	68
Pareto Global A	2009M01 - 2017M12	108
Pareto Global B *	2012M12 - 2017M12	61
Pareto Global C *	2012M12 - 2017M12	61
Pareto Global D	2009M01 - 2017M12	108
Pluss Utland Aksje	2009M01 - 2017M12	108
PLUSS Utland Etisk	2009M01 - 2017M12	108
SEB 1 Global Fund C NOK C *	2015M03 - 2017M12	34
Sector Global Equity Kernel A NOK *	2016M01 - 2017M12	24
Sector Global Equity Kernel P NOK *	2015M04 - 2017M12	33
Sector Global Equity Kernel P NOK UH *	2015M05 - 2017M12	32
SKAGEN Focus A NOK *	2015M06 - 2017M12	31
SKAGEN Global A NOK	2009M01 - 2017M12	108
SKAGEN Global B NOK *	2014M02 - 2017M12	47
Skagen Global II NOK	2009M01 - 2017M12	108
Storebrand Global Multifaktor	2009M01 - 2017M12	108
Storebrand Global Solutions *	2012M11 - 2017M12	62
Storebrand Global Verdi	2009M01 - 2017M12	108
STOREBRAND INTL.INV.FD. GLOBAL SRI **	2009M01 - 2013M08	56
Terra Global **	2009M01 - 2013M12	60
Vekterfond Aksjer I Open Fund	2009M01 - 2017M12	108

Appendix 2:

Results from Durbin Watson, Breusch-Pagan and Shapiro Wilk tests, in alphabetical order. The Durbin Watson shows the autocorrelation, Breusch-Pagan shows heteroscedasticity and Shapiro-Wilk shows the normality.

	Autocorrelation	Heteroscedasticity	Normality
Fund Name	**Durbin Watson estimate**	**Breusch-Pagan p-value**	**Shapiro-Wilk p-value**
Alfred Berg Global Quant Open Fund	2,1058	0,2207	0,1460
Arctic Global Equities A	2,3348	0,1388	0,0441
Arctic Global Equities B	2,3410	0,1516	0,0426
Arctic Global Equities H	1,3405	0,4311	0,4170
Arctic Global Equities I	2,1614	0,2511	0,0277
C WorldWide Globale Aksjer	2,4653	0,6966	0,0410
C WorldWide Globale Aksjer Etisk	2,3122	0,7638	0,0171
C WorldWide Stabile Aksjer	2,0811	0,7368	0,3010
CARNEGIE WORLD WIDE ETISK II	2,0378	0,8152	0,2469
Danica Pensjon Norge - Aksjer	1,3709	0,0000	0,7528
Danske Invest Investeringsprofil Aksjer Open Fund	2,0863	0,5796	0,0992
Delphi Global Open Fund	2,4762	0,5187	0,0551
DNB AM Global Valutasikret	2,1507	0,4147	0,4800
DNB Fund Global Value & Momentum	2,4059	0,4492	0,0533
DNB Global (I)	2,1924	0,6235	0,0703
DNB Global (III)	2,1358	0,9592	0,0812
DNB Global (IV)	2,1678	0,8653	0,0966
DNB Global Etisk (V)	2,0895	0,3777	0,1454
DNB GLOBAL ETISK IV	1,9880	0,6134	0,2632
DNB GLOBAL II	2,1917	0,3681	0,2267
DNB GLOBAL SELEKTIV I	2,0990	0,4220	0,2243
DNB GLOBAL V	2,1464	0,1525	0,1756
DNB GLOBALSPAR	2,1374	0,0603	0,1935
Eika Global	1,6521	0,1348	0,0589
Forte Global	2,0795	0,9258	0,5239
FRAM Global Open Fund	2,0482	0,9795	0,4480
Handelsbanken Global Tema (A1 NOK)	2,1711	0,9727	0,3935
Holberg Global A	2,2274	0,5010	0,0605
HOLBERG GLOBAL B	2,2369	0,4836	0,0612
KLP AksjeGlobal Lavbeta I	1,6248	0,7031	0,5483
KLP AksjeGlobal Lavbeta II	1,8378	0,6585	0,8804
KLP Framtid	1,9849	0,2058	0,1576
Landkreditt Aksje Global Open Fund	2,2458	0,3614	0,0442
Nordea 1 - Global Value BP NOK	1,9471	0,9354	0,6548
Nordea Global NOK	2,6507	0,9700	0,0122
NORDEA INTERNASJONALE AKSJER	2,5497	0,4195	0,0121
NORDEA INTERNASJONALE AKSJER II	2,5599	0,4313	0,0129
NORDEA INTERNASJONALE AKSJER III	2,5706	0,4328	0,0106
Nordea Plan 100	2,0099	0,2845	0,0357
Nordea Stabile Aksjer Global Etisk	2,1558	0,3834	0,0567
ODIN FORVALTNING AS GLB. SMB NOK	2,6072	0,0091	0,3151
ODIN Global	2,0038	0,0000	0,0075
ODIN Global A	2,4251	0,1462	0,5258
ODIN Global B	2,4271	0,1454	0,5291
ODIN Global D	2,4242	0,1463	0,5269
ODIN GLOBAL II	1,9344	0,7875	0,2487
Pareto Global A	2,0181	0,8044	0,1753
Pareto Global B	2,0553	0,7405	0,7081
Pareto Global C	2,0508	0,7385	0,7088
Pareto Global D	2,0075	0,7312	0,1992
Pluss Utland Aksje	2,4496	0,0695	0,0444
PLUSS Utland Etisk	2,6743	0,0000	0,0182
SEB 1 Global Fund C NOK C	2,2650	0,8507	0,1605
Sector Global Equity Kernel A NOK	2,2095	0,6961	0,8163
Sector Global Equity Kernel P NOK	1,9731	0,4062	0,7157
Sector Global Equity Kernel P NOK UH	2,0902	0,8485	0,1049
SKAGEN Focus A NOK	2,2898	0,4205	0,5735
SKAGEN Global A NOK	1,9918	0,9864	0,1743
SKAGEN Global B NOK	1,9738	0,5057	0,4406
Skagen Global II NOK	2,0287	0,9666	0,1728
Storebrand Global Multifaktor	2,0320	0,1057	0,0286
Storebrand Global Verdi	1,7404	0,5780	0,0349
STOREBRAND SRI	2,6571	0,5628	0,6929
Storebrand Trippel Smart	1,9733	0,0511	0,7715
Terra Global	1,8599	0,0200	0,1171
Vekterfond Aksjer I Open Fund	2,0736	0,5207	0,1011

Appendix 3:

The table shows each fund's R^2 measure and tracking error measure, ranked from most active to least active. The bottom of the table shows the average and median from both measures.

Fund Name	R^2
KLP Framtid	0,2670
Sector Global Equity Kernel A NOK	0,4707
Sector Global Equity Kernel P NOK	0,6135
ODIN GLOBAL II	0,6210
KLP AksjeGlobal Lavbeta II	0,6487
Arctic Global Equities H	0,6705
FRAM Global Open Fund	0,7649
DNB AM Global Valutasikret	0,8052
SKAGEN Focus A NOK	0,8211
Nordea 1 - Global Value BP NOK	0,8251
Danica Pensjon Norge - Aksjer	0,8264
ODIN Global A	0,8321
ODIN Global B	0,8321
ODIN Global D	0,8326
Sector Global Equity Kernel P NOK UH	0,8556
C WorldWide Stabile Aksjer	0,8564
Pareto Global B	0,8628
Pareto Global C	0,8642
CARNEGIE WORLD WIDE ETISK II	0,8652
SEB 1 Global Fund C NOK C	0,8741
Nordea Stabile Aksjer Global Etisk	0,8789
Forte Global	0,8810
ODIN FORVALTNING AS GLB. SMB NOK	0,8813
Terra Global	0,8875
C WorldWide Globale Aksjer	0,8881
ODIN Global	0,8911
C WorldWide Globale Aksjer Etisk	0,8935
Eika Global	0,8950
DNB Fund Global Value & Momentum	0,8994
Storebrand Global Solutions	0,9074
Pareto Global A	0,9095
Arctic Global Equities I	0,9119
Holberg Global A	0,9119
HOLBERG GLOBAL B	0,9127
Pareto Global D	0,9150
Handelsbanken Global Tema (A1 NOK)	0,9188
Delphi Global Open Fund	0,9189
Arctic Global Equities A	0,9212
Arctic Global Equities B	0,9215
SKAGEN Global B NOK	0,9242
Skagen Global II NOK	0,9261
Nordea Plan 100	0,9277
SKAGEN Global A NOK	0,9303
PLUSS Utland Etisk	0,9309
Vekterfond Aksjer I Open Fund	0,9325
Danske Invest Investeringsprofil Aksjer Open F	0,9327
Pluss Utland Aksje	0,9341
NORDEA INTERNASJONALE AKSJER II	0,9463
NORDEA INTERNASJONALE AKSJER III	0,9464
NORDEA INTERNASJONALE AKSJER	0,9466
Storebrand Global Verdi	0,9499
KLP AksjeGlobal Lavbeta I	0,9521
STOREBRAND GLOBAL SRI	0,9543
Nordea Global NOK	0,9575
Alfred Berg Global Quant Open Fund	0,9641
DNB Global Etisk (V)	0,9700
DNB Global (IV)	0,9726
Landkreditt Aksje Global Open Fund	0,9729
DNB Global (III)	0,9732
DNB Global (I)	0,9734
DNB GLOBAL II	0,9802
Storebrand Global Multifaktor	0,9809
DNB GLOBAL ETISK IV	0,9830
DNB GLOBAL SELEKTIV I	0,9844
DNB GLOBAL V	0,9857
DNB GLOBALSPAR	0,9861
AVERAGE	0,8784
MEDIAN	0,9119

Fund Name	TE
ODIN FORVALTNING AS GLB. SMB NOK	12,25 %
Arctic Global Equities H	10,06 %
FRAM Global Open Fund	9,81 %
Danica Pensjon Norge - Aksjer	9,64 %
Sector Global Equity Kernel P NOK	9,39 %
DNB AM Global Valutasikret	9,32 %
KLP AksjeGlobal Lavbeta II	8,84 %
Sector Global Equity Kernel A NOK	8,78 %
SKAGEN Focus A NOK	8,24 %
Nordea 1 - Global Value BP NOK	7,34 %
ODIN Global	7,27 %
C WorldWide Stabile Aksjer	6,73 %
DNB Fund Global Value & Momentum	6,53 %
Terra Global	6,46 %
STOREBRAND GLOBAL SRI	6,29 %
ODIN Global B	6,27 %
ODIN Global A	6,27 %
ODIN Global D	6,27 %
Skagen Global II NOK	6,23 %
SKAGEN Global A NOK	5,98 %
KLP Framtid	5,91 %
Nordea Stabile Aksjer Global Etisk	5,91 %
Holberg Global A	5,86 %
HOLBERG GLOBAL B	5,86 %
Pareto Global D	5,84 %
Delphi Global Open Fund	5,81 %
Nordea Plan 100	5,80 %
CARNEGIE WORLD WIDE ETISK II	5,77 %
Pareto Global A	5,76 %
ODIN GLOBAL II	5,76 %
Eika Global	5,60 %
C WorldWide Globale Aksjer	5,59 %
Forte Global	5,58 %
Pareto Global B	5,52 %
Pareto Global C	5,49 %
C WorldWide Globale Aksjer Etisk	5,40 %
Arctic Global Equities I	5,31 %
PLUSS Utland Etisk	5,07 %
Danske Invest Investeringsprofil Aksjer Open Fu	4,81 %
Vekterfond Aksjer I Open Fund	4,81 %
Arctic Global Equities A	4,80 %
Arctic Global Equities B	4,80 %
SKAGEN Global B NOK	4,79 %
Pluss Utland Aksje	4,70 %
Handelsbanken Global Tema (A1 NOK)	4,70 %
Sector Global Equity Kernel P NOK UH	4,42 %
NORDEA INTERNASJONALE AKSJER II	4,12 %
Storebrand Global Solutions	4,11 %
NORDEA INTERNASJONALE AKSJER III	4,11 %
NORDEA INTERNASJONALE AKSJER	4,07 %
Storebrand Global Verdi	4,05 %
SEB 1 Global Fund C NOK C	3,82 %
Nordea Global NOK	3,28 %
KLP AksjeGlobal Lavbeta I	3,28 %
DNB Global Etisk (V)	3,25 %
Alfred Berg Global Quant Open Fund	3,07 %
DNB Global (IV)	2,95 %
DNB Global (I)	2,91 %
DNB GLOBALSPAR	2,89 %
DNB Global (III)	2,88 %
DNB GLOBAL ETISK IV	2,80 %
DNB GLOBAL V	2,67 %
DNB GLOBAL II	2,65 %
DNB GLOBAL SELEKTIV I	2,64 %
Landkreditt Aksje Global Open Fund	2,49 %
Storebrand Global Multifaktor	2,31 %
AVERAGE	5,48 %
MEDIAN	5,58 %

Appendix 4: Net individual fund performance

The table shows the individual fund performance from the Fama and French five-factor model, ranked by the best to worst of the *t(α)*, net of fees.

Rank	α	**mkt-rf**	**SMB**	**HML**	**RMW**	**CMA**	R^2
1	0,0016	1,0098	0,0911	0,1580	-0,2690	-0,1830	0,9499
StorebrandGlobalVerdi	*(1,368)*	*(34,379)*	*(1,086)*	*(2,078)*	*(-2,323)*	*(-1,755)*	
2	0,0007	1,0268	0,1411	-0,0013	-0,0987	0,0600	0,9809
StorebrandGlobalMultifaktor	*(1,042)*	*(59,710)*	*(2,873)*	*(-0,029)*	*(-1,456)*	*(0,983)*	
3	0,0007	1,0774	0,1318	-0,0566	-0,0345	-0,0523	0,9830
DNBGLOBALETISKIV	*(0,692)*	*(43,811)*	*(1,769)*	*(-0,845)*	*(-0,329)*	*(-0,613)*	
4	0,0005	1,0628	0,1405	-0,1030	-0,1319	0,0774	0,9857
DNBGLOBALV	*(0,451)*	*(43,406)*	*(1,907)*	*(-1,592)*	*(-1,267)*	*(0,939)*	
5	0,0126	0,7065	-1,1625	-0,7424	-1,2870	0,7942	0,2670
KLPFramtid	*(0,439)*	*(0,622)*	*(-0,493)*	*(-0,473)*	*(-0,611)*	*(0,482)*	
6	0,0009	0,7947	0,3438	-0,1305	0,1725	0,2128	0,8556
SectorGlobalEquityKernelPNOKUH	*(0,437)*	*(10,789)*	*(1,932)*	*(-0,743)*	*(0,711)*	*(0,917)*	
7	0,0008	1,1081	0,1524	0,1716	-0,2482	-0,6648	0,9543
STOREBRANDSRI	*(0,368)*	*(22,483)*	*(1,025)*	*(1,312)*	*(-1,179)*	*(-4,019)*	
8	0,0009	0,7261	0,1421	-1,0580	-0,7096	0,6713	0,6210
ODINGLOBALII	*(0,289)*	*(9,378)*	*(0,658)*	*(-5,181)*	*(-2,304)*	*(2,416)*	
9	0,0003	1,0850	0,1635	-0,2088	-0,3970	-0,4504	0,9189
DelphiGlobalOpenFund	*(0,217)*	*(27,125)*	*(1,431)*	*(-2,017)*	*(-2,518)*	*(-3,172)*	
10	0,0004	0,9909	0,3716	-0,2731	0,0299	-0,3860	0,9188
HandelsbankenGlobalTemaA1NO	*(0,177)*	*(12,405)*	*(1,915)*	*(-1,327)*	*(0,104)*	*(-1,524)*	
Median	-0,0019	1,1508	0,1642	0,2711	0,1264	-0,6752	0,9261
SkagenGlobalIINOK	*(-1,192)*	*(28,234)*	*(1,411)*	*(2,571)*	*(0,786)*	*(-4,666)*	
57	-0,0050	1,1433	0,0296	-0,2655	0,1516	0,1707	0,8564
CWorldWideStabileAksjer	*(-2,419)*	*(21,539)*	*(0,195)*	*(-1,933)*	*(0,724)*	*(0,906)*	
58	-0,0051	1,1960	0,3766	0,4480	0,4903	-0,4070	0,8628
ParetoGlobalB	*(-2,437)*	*(16,635)*	*(2,213)*	*(2,678)*	*(1,967)*	*(-1,675)*	
59	-0,0019	1,0207	0,0828	0,0568	0,1616	0,0386	0,9729
LandkredittAksjeGlobalOpenFu	*(-2,488)*	*(50,953)*	*(1,447)*	*(1,095)*	*(2,046)*	*(0,543)*	
60	-0,0062	1,1340	0,5507	-0,0054	-0,1207	0,0074	0,8994
DNBFundGlobalValueMomentum	*(-2,880)*	*(20,851)*	*(3,810)*	*(-0,0378)*	*(-0,556)*	*(0,035)*	
61	-0,0053	1,1079	0,1357	0,6080	0,4862	-0,9093	0,9242
SKAGENGlobalBNOK	*(-3,066)*	*(16,653)*	*(0,990)*	*(4,404)*	*(2,485)*	*(-4,123)*	
62	-0,0059	1,1336	0,4204	0,2138	0,2150	-0,4815	0,8810
ForteGlobal	*(-3,172)*	*(18,924)*	*(2,662)*	*(1,388)*	*(0,987)*	*(-2,139)*	
63	-0,0055	1,2187	0,1726	0,2259	0,1634	-0,3647	0,9119
ArcticGlobalEquitiesI	*(-3,262)*	*(23,104)*	*(1,257)*	*(1,623)*	*(0,838)*	*(-1,843)*	
64	-0,0058	1,1687	0,0695	0,2658	0,1805	-0,5518	0,9215
ArcticGlobalEquitiesB	*(-3,832)*	*(23,912)*	*(0,552)*	*(2,114)*	*(1,027)*	*(-3,007)*	
65	-0,0034	1,0144	0,1287	-0,1836	0,2073	0,2758	0,9641
AlfredBergGlobalQuantOpenFu	*(-3,947)*	*(46,165)*	*(2,051)*	*(-3,229)*	*(2,393)*	*(3,535)*	
66	-0,0064	1,1687	0,0725	0,2659	0,1830	-0,5525	0,9212
ArcticGlobalEquitiesA	*(-4,268)*	*(23,869)*	*(0,574)*	*(2,111)*	*(1,039)*	*(-3,006)*	

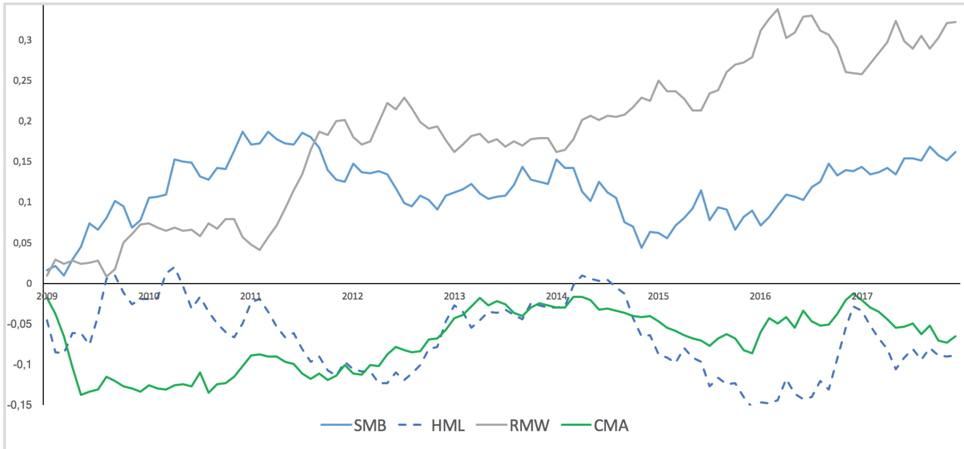
Appendix 5: Gross individual fund performance

The table shows the individual fund performance from the Fama and French five-factor model, ranked by best to worst of the *t(α)*, gross of fees.

Rank	α	mkt-rf	SMB	HML	RMW	CMA	R^2
1	0,0013	1,0274	0,1412	-0,0013	-0,0988	0,0600	0,9809
StorebrandGlobalMultifaktor	*(1,974)*	*(59,710)*	*(2,873)*	*(-0,029)*	*(-1,456)*	*(0,983)*	
2	0,0022	1,0105	0,0911	0,1581	-0,2692	-0,1831	0,9499
StorebrandGlobalVerdi	*(1,914)*	*(34,379)*	*(1,086)*	*(2,078)*	*(-2,323)*	*(-1,755)*	
3	0,0020	1,0868	0,1638	-0,2091	-0,3977	-0,4512	0,9189
DelphiGlobalOpenFund	*(1,285)*	*(27,125)*	*(1,431)*	*(-2,017)*	*(-2,517)*	*(-3,172)*	
4	0,0012	1,0780	0,1319	-0,0566	-0,0345	-0,0523	0,9830
DNBGLOBALETISKIV	*(1,155)*	*(43,811)*	*(1,769)*	*(-0,845)*	*(-0,329)*	*(-0,613)*	
5	0,0011	1,0535	0,1383	-0,0966	-0,1228	0,0368	0,9844
DNBGLOBALSELEKTIVI	*(1,013)*	*(42,630)*	*(1,874)*	*(-1,469)*	*(-1,154)*	*(0,440)*	
6	0,0012	0,8153	-0,0122	-0,0991	0,4725	0,3314	0,8789
NordeaStabileAksjerGlobalEti	*(0,936)*	*(24,574)*	*(-0,128)*	*(-1,155)*	*(3,613)*	*(2,814)*	
7	0,0009	1,0632	0,1405	-0,1031	-0,1320	0,0774	0,9857
DNBGLOBALV	*(0,835)*	*(43,406)*	*(1,907)*	*(-1,592)*	*(-1,267)*	*(0,939)*	
8	0,0006	1,0518	0,1005	0,0234	-0,1433	-0,0099	0,9732
DNBGlobalIII	*(0,702)*	*(49,707)*	*(1,663)*	*(0,426)*	*(-1,718)*	*(-0,132)*	
9	0,0016	0,9921	0,3720	-0,2734	0,0300	-0,3870	0,9188
HandelsbankenGlobalTemaA1NO	*(0,675)*	*(12,405)*	*(1,915)*	*(-1,327)*	*(0,104)*	*(-1,524)*	
10	0,0006	1,0634	0,1491	0,0744	-0,1213	-0,1171	0,9700
DNBGlobalEtiskV	*(0,643)*	*(46,507)*	*(2,283)*	*(1,257)*	*(-1,346)*	*(-1,443)*	
Median	-0,0007	1,0631	0,0765	0,0502	-0,0398	-0,3117	0,9464
NORDEAINTERNASJONALEAKSJERIII	*(-0,578)*	*(34,444)*	*(0,867)*	*(0,628)*	*(-0,327)*	*(-2,844)*	
57	-0,0037	1,1976	0,3772	0,4486	0,4910	-0,4076	0,8628
ParetoGlobalB	*(-1,794)*	*(16,635)*	*(2,213)*	*(2,678)*	*(1,966)*	*(-1,675)*	
58	-0,0085	1,2471	0,2708	0,3794	1,0008	0,4826	0,6487
KLPAksjeGlobalLavbetaII	*(-2,083)*	*(7,675)*	*(0,830)*	*(1,104)*	*(2,052)*	*(0,918)*	
59	-0,0076	1,5128	0,2980	0,5936	0,2372	0,1873	0,8052
SectorGlobalEquityKernelPNOKUH	*(-2,111)*	*(10,880)*	*(1,040)*	*(2,057)*	*(0,580)*	*(0,406)*	
60	-0,0043	1,1355	0,4211	0,2141	0,2154	-0,4823	0,8810
ForteGlobal	*(-2,278)*	*(18,924)*	*(2,663)*	*(1,388)*	*(0,987)*	*(-2,139)*	
61	-0,0049	1,1354	0,5514	-0,0054	-0,1208	0,0074	0,8994
DNBFundGlobalValueMomentum	*(-2,296)*	*(20,852)*	*(3,810)*	*(-0,037)*	*(-0,556)*	*(0,035)*	
62	-0,0021	1,0158	0,1289	-0,1839	0,2076	0,2761	0,9641
AlfredBergGlobalQuantOpenFu	*(-2,391)*	*(46,165)*	*(2,051)*	*(-3,229)*	*(2,393)*	*(3,535)*	
63	-0,0046	1,1086	0,1358	0,6084	0,4866	-0,9099	0,9242
SKAGENGlobalBNOK	*(-2,677)*	*(16,653)*	*(0,990)*	*(4,404)*	*(2,485)*	*(-4,123)*	
64	-0,0048	1,2194	0,1727	0,2261	0,1635	-0,3649	0,9119
ArcticGlobalEquitiesI	*(-2,888)*	*(23,104)*	*(1,257)*	*(1,623)*	*(0,837)*	*(-1,843)*	
65	-0,0049	1,1697	0,0696	0,2660	0,1806	-0,5523	0,9215
ArcticGlobalEquitiesB	*(-3,279)*	*(23,912)*	*(0,552)*	*(2,114)*	*(1,027)*	*(-3,007)*	
66	-0,0050	1,1704	0,0726	0,2663	0,1833	-0,5534	0,9212
ArcticGlobalEquitiesA	*(-3,302)*	*(23,868)*	*(0,574)*	*(2,111)*	*(1,039)*	*(-3,006)*	

Appendix 6: Cumulative factor returns

The graph shows the cumulative factor returns from 2009 to 2017.



Appendix 7: MSCI World Index

MSCI WORLD INDEX		
DEVELOPED MARKETS		
Americas	**Europe & Middle East**	**Pacific**
Canada United States	Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Israel, Italy, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom	Australia Hong Kong Japan New Zealand Singapore