Do Managers of Active Norwegian Funds Possess Stock-Picking Skills?

An empirical analysis of Norwegian active mutual funds between 1987 and 2019

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December 1st, 2021

Master thesis, MSc Business Administration, Analytical Finance

Abstract

This thesis evaluates fund managers of active Norwegian funds using a dataset consisting of 107 actively managed mutual funds from 1987-2019. Using the Carhart (1997) four-factor model as the primary performance model, I examine the funds' performance on an aggregate and individual level. A bootstrap procedure similar to Kosowski et al. (2006) is implemented to distinguish between skill and luck among individual fund managers. The aggregate fund fails to produce a significant risk-adjusted excess return net of fees, with a yearly alpha of 0.04 %. Using the parametric p-value, there are 12 significant negative alphas and 7 significant positive alphas on the individual level. Analyzing the bootstrapped results, I find no evidence of skilled fund managers in the top-performing funds. I do, however, find evidence of a lack of skill among the worst-performing funds. When considering my results and the cost differences between active and passive funds, the majority of investors are most likely best off investing in a passive, low-cost index fund.

Preface

This thesis concludes my Master of Science (M.Sc.) in Economics and Business Administration at the University of Agder (UiA). With a specialization in Analytical Finance and a curiosity in the stock market, I wanted to write a thesis related to stocks. In the end, I landed on active mutual funds. Therefore, this thesis aims to evaluate the performance of Norwegian active mutual funds and assess the actual skill of their fund managers. The work has been challenging, interesting, and frustrating, but in the very end, rewarding.

I would like to thank professor Valeriy Ivanovich Zakamulin for his help and feedback, especially regarding the use of Rstudio. Thank you to the members of the TITLON-database and Bernt A. Ødegaard for access to the analytical data needed for this thesis. Lastly, I would like to thank my fellow students, friends, and family for their support and helpful comments throughout the working progress of this thesis.

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1. Introduction

Fund investments have become one of the most popular ways to invest money, both for private individuals and institutions. The investor's dilemma is what type of fund they should invest in. The two alternatives are primarily passively managed index funds or actively managed funds. An index fund follows a given index, for instance, the OSEBX (Oslo stock exchange benchmark index). An actively managed fund, on the other hand, has fund managers actively analyzing which stocks to buy in order to beat the benchmark index. For this extra return, the actively managed funds charge a higher price. However, since the 1960s, the discussion has increasingly revolved around the actual profitability of actively managed mutual funds. The extra costs associated with active management mean the fund managers must perform significantly better than the market to actually create excess return for their customers. The question is, do they?

According to the efficient market hypothesis (EMH) by Fama (1970), all deviations from the market will be a game of chance because the current stock prices reflect all available information in the market. Some funds might perform better than the market in the short term, and some might perform worse, but according to Fama (1970), this is caused by luck rather than stock-picking skills or lack thereof. The EMH has been heavily discussed but is still a hypothesis yet to be rejected. Regardless of Fama being correct or not in his assumption of efficient markets, large amounts of money are every year invested into actively managed mutual funds, whose job is to beat the market persistently.

Recent statistics show that active mutual funds in Norway earn big money at the customer's expense. Customers have paid a higher fee for actively managed funds, while most fund managers have not managed to outperform the benchmark index. Aggregated, the customers have lost almost 34 billion NOK, investing in expensive active mutual funds between 2003 and 2020. (Linderud & Bakken, 2020) Only 45.7 % of active mutual funds managed to outperform the benchmark index in this period. (Linderud & Bakken, 2020) Until 2011 the active funds did manage to beat the index, but during the last decade, they have underperformed. One reason for this could be the change in prices for active and passive funds, where aggregated passive funds have had a more significant price decrease than aggregated active funds. (Linderud & Bakken, 2020) Parallel to the poor performance in 2011-2020, however, assets under management

(AUM) for Norwegian funds have increased by 214%. (VFF, 2020) There has been a clear shift towards index funds, but the distribution between active and passive funds is still heavily skewed towards actively managed funds. In 2011 passive funds made up 14 % of the global fund market, and by 2020 this number had increased to 31 % (Statista, 2020). We have seen a similar development in the Norwegian market, with 26 % of the total AUM in 2019 being placed in index funds compared to 13 % in 2011 (VFF, 2019). One reason for this development could be the increased publicity on the subject leading to customers being more aware when choosing their saving methods.

The ongoing discussion among academics and media on the profitability of active mutual funds is what inspired me to write this thesis. The statistics suggest that index funds are the best choice when it comes to fund investing as the skill of individual fund managers is questionable. Variations in performance among mutual funds, however, could have several reasons. For example, an inappropriate benchmark could have been used in the performance evaluation, too few risk factors may have been analyzed, or different biases may apply. Therefore, the purpose of this thesis is twofold. First, I want to find out if Norwegian actively managed mutual funds are able to produce significant risk-adjusted excess returns. This is done by implementing several different factor models and then using OLS estimation to control for the benchmark index and other relevant factors that explain systematic risk. Secondly, after assessing the funds' performances, I will determine if we can rule out the possibility of the best and worst fund performances being a result of luck. To do this, I will implement a bootstrap procedure similar to Kosowski et al. (2006).

The reason for the bootstrap procedure is that positive alpha values can appear due to luck. This is because of the parametric one-sample t-test approach. Using this approach with a 5 % significance level, it is expected that 2.5 % of the sample funds will have a significant alpha higher than zero due to luck alone. On the other hand, by luck alone (or rather misfortune), we also expect that 2.5 % is expected to have a significant alpha lower than zero. This is because the belonging p-value of this test ignores the effects of chance. As an example, we can imagine a collection of 1000 funds and testing the hypothesis of zero abnormal performance ($H_0\colon \alpha_i = 0,\ H_1\colon \alpha_i \neq 0$). 50 funds out of 1000 are expected to have statistically significant alphas just by chance, even if their true alpha is zero (Steiman, 2012). The implementation of the bootstrap methodology enables me to analyze the funds under the null hypothesis of zero abnormal performance ($\alpha_i = 0$). By running 10 000 bootstrap simulations, I get a cross-section of alpha estimates representing the abnormal return of the funds that is solely due to luck. I.e., the bootstrapped cross-section represents the alpha one expects to get exclusively from luck. Comparing this “lucky distribution” to the actual distribution of funds’ alpha enables us to distinguish skill from luck.

Summed up, the thesis seeks to answer the following research questions:

1. Are there Norwegian active mutual funds that manage to produce significant risk-adjusted excess return net of fees?
2. Can we conclude that the best and worst performances are not a result of luck but rather a result of fund managers’ stock-picking skills and lack thereof, respectively?

The thesis is split up into six sections, excluding the introduction. The following section will review relevant historical literature, beginning with international research because of the relevant theory and methodology. I will also look at relevant Scandinavian research as the dataset will consist exclusively of Norwegian active mutual funds. In the third and fourth sections, respectively, the relevant theory and methodology will be presented. The fifth section will deal with the data selection and explain the criteria I followed in the collection process. Finally, in the sixth section, I will present the empirical results before making final remarks and concluding according to my results in the seventh and last section.

2. Literature review

This section presents an overview of previous research on active mutual fund performance, bootstrap analyses, and the question of luck and skill among mutual funds. The purpose of this section is to inform the reader about the most relevant research on the subject of active mutual fund performance evaluation. I will first go through the major international research involving mutual fund performance evaluation. Then, I will present the literature on bootstrapping and its importance in deciding on luck versus skill in fund management. Lastly, I will highlight the leading Scandinavian research on the topic as I use data on the Norwegian fund market.

2.1 International research

The field of portfolio theory was introduced by Markowitz (1952), where he, among other things, developed the concept of diversification. Building on this, the famous capital asset pricing model (CAPM) was developed by Jack Treynor (1962), William Sharpe (1964), John Lintner (1965), and Jan Mossin (1966). Sharpe (1966) introduced the Sharpe ratio (return-to-risk ratio) and used this ratio to evaluate the risk-adjusted performance of 34 open-end mutual funds in the period 1945-1963. He found that 11 funds outperformed the benchmark index while the other 23 underperformed it, concluding that actively managed mutual funds were a lousy investment over an efficient US market.

Another early publication on active mutual fund performances was written by Jensen (1968). In his paper, he introduced the single-factor model based on the previously mentioned CAPM model. Jensen evaluates 115 actively managed mutual funds from 1945-1964 using the new performance measure of Jensen's alpha. The alpha represents the fund manager's ability to pick profitable stocks and describes the abnormal risk-adjusted return of a mutual fund. An actively managed fund aims to beat the market and produce a positive alpha, whereas a passive index fund should have an alpha equal to zero. In his research, Jensen (1968) concluded that the funds on average and on an individual level were not able to outperform the benchmark index, both gross and net of transaction costs.

However, Jensen (1968) later received some resistance on this when Ippolito (1989) argued against him. Conducting a similar study using a sample of 143 US mutual funds from 1965-1984, Ippolito found evidence of mutual funds outperforming the S&P500 index net of cost. Jensen (1968) was also criticized for using the CAPM proxy as a benchmark for performance because this required the complete knowledge of the true market portfolio's composition. This critique was put forward by Roll (1977), and the issue of choosing a correct benchmark to evaluate abnormal fund performance was further addressed by Lehmann and Modest (1987), Grinblatt and Titman(1989), and Connor and Korajczyk (1991). In their research, Lehmann and Modest (1987) found that the estimated performance of a fund was highly sensitive to the chosen benchmark. Therefore, they stressed the importance of using an appropriate benchmark. Following these findings, Elton et al. (1996a) investigated the mutual funds in Ippolito's (1989) portfolio and found that the funds were heavily invested in small stocks not listed on the S&P500 benchmark. These stocks outperformed the benchmark significantly during the sample period, and when accounting for the performance of these non-S&P500 assets, Elton et al. (1996a) found that the positive alpha became negative.

This sensitivity to the choice of benchmark led to the development of the multifactor model, which controlled for various anomalies in the equity market. The most widespread multifactor models are the Fama and French (1993) three-factor model and the Carhart (1997) four-factor model. The Fama and French (1993, 1996) three-factor model added two extra factors to Jensen's (1968) single-factor model, the size factor (SMB) and the value factor (HML). Carhart (1997) added the one-year momentum factor (PR1YR) of Jegadeesh and Titman (1993) to make his four-factor model. Carhart (1997) finds that the momentum factor is significant in explaining fund returns but concludes that it is not possible to determine whether it is due to skill or if some investors possess more information than others regarding market timing. Carhart (1997) also argues that the positive excess returns in Elton et al. (1996a) can be explained by Elton et al. not including a momentum variable in their models.

Some studies on mutual fund performance evaluation involve larger fund samples. Daniel et al. (1997) evaluated 2500 US equity mutual funds in 1975-1994 to assess if fund managers' stock-picking skills can justify their fees. Using a benchmark of 125 passive portfolios, Daniel et al. (1997) examined whether funds' excess returns were attributed to "characteristic selectivity" and "characteristic timing". They did find that some mutual funds exhibited stock-picking skills with an annual positive alpha, but most of these were characterized as aggressive-growth funds. One year later, Blake and Timmermann (1998) published their research on 2300 UK mutual funds from 1972-1995. They found that the average UK mutual fund underperforms on a risk-adjusted basis by 1.8 %. They also found evidence for funds overperforming in their first year of existence, while underperformance intensified as the fund's termination date approached. Otten and Bams (2002) evaluated 506 mutual funds collected from Germany, France, Italy, Netherlands, and the UK. Controlling for survivorship bias, they applied Carhart's (1997) four-factor model to the net returns of the European countries and found that only Germany produced a negative alpha, net of costs. However, Germany's alpha was not significant, and after accounting for transaction costs, only the UK funds had a significantly positive alpha. A more recent study is Huij and Verbeek (2007), who investigated short-term performance persistence among funds. They used data from 6400 US funds between 1984 and 2003 and sorted the funds into decile portfolios based on 12-month ranking periods. They discovered that the top decile of funds earned a statistically significant alpha of 0.26 % per month.

2.1.1 Skill versus luck

Kosowski et al. (2006) applied a new bootstrap method to distinguish lucky fund managers from skilled fund managers. The study was done in the American fund market and covered the monthly returns from 1788 mutual funds in 1975-2002. Using the new bootstrap procedure, they concluded that the performances by the top and bottom funds could not be explained solely by luck and that good stock-pickers exist among the top ten percent as well as bad ones in the bottom ten percent. The bootstrap methodology has three main advantages when it comes to evaluating funds. Firstly, it removes the requirement for specifying the exact shape of the distribution in which returns are drawn. Secondly, it eliminates the need to estimate correlations between portfolio returns. Thirdly, you don't have to control explicitly for "data snooping" biases (Kosowski et al., 2006). The same bootstrap methodology as Kosowski et al. (2006) is applied to distinguish luck from skill in my thesis. The procedure will be explained in full in the methodology section.

The bootstrap method of Kosowski et al. (2006) has been tried and modified in many different studies. Cuthbertson et al. (2008) used the bootstrap methodology of Kosowski et al. (2006) in a study on UK mutual funds. They analyzed a total of 842 mutual funds between 1975 and 2002 and came to the same conclusion as Kosowski et al. (2006) did for the US fund market. A relatively small number of top-performing funds exhibited stock-picking abilities, while most of the poorest performing funds exhibited a lack of stock-picking abilities. Cuthbertson et al. (2008) also concluded that many UK equity investors would be better off holding passive index funds due to their lower transaction costs. Fama and French (2010) used a modified version of the bootstrap of Kosowski et al. (2006). They used a sample size of 5238 US mutual funds with different sizes of assets under management in the period 1984 to 2006. The results they got contradicted Kosowski et al. (2006) as Fama and French (2010) did not find any evidence of superior abnormal performance in the top ten percent of funds. However, both studies concurred that the bottom funds' poor performance was due to a lack of skill.

2.2 Scandinavian research

The research I have chosen to present as most relevant to my thesis is a Swedish study by Dahlquist et al. (2000), a Danish study by Christensen (2013), and the Norwegian studies by Sørensen (2009) and Gallefoss et al. (2015).

Dahlquist et al. (2000) studied the Swedish mutual fund market between 1993 and 1997. They performed their research on several different types of actively managed funds, comparing many different attributes. They found that good performance occurs among small funds, low-fee funds, funds with high trading activity, and in some cases, funds with good past performance. They also discovered evidence supporting that actively managed funds performed better than passively managed index funds. Christensen (2013) examined 71 Danish mutual funds from 2001 to 2010, looking at significant alphas. Half of the funds performed neutrally, whereas the other half showed significant abnormal performance. Furthermore, 41 % of the funds performed significantly negative, while 7 % performed significantly positive. They also found that only 14 % of the funds analyzed possess market timing abilities.

The most acknowledged research on the Norwegian fund market is probably by Sørensen (2009). He examined all Norwegian equity mutual funds listed on the Oslo stock exchange between 1982 and 2008 and controlled for the factors in the Fama-French three-factor model. He found no evidence of abnormal performance for the equally weighted portfolio of funds. Using a bootstrap methodology based on Fama and French (2010) to evaluate individual funds, he found no clear evidence of overperformance among top funds. He did, however, find some indication of underperformance among bottom funds, but these results were not statistically significant. Another Norwegian study done by Gallefoss et al. (2015) examined Norwegian mutual funds between 2000 and 2010. They used daily return data to evaluate the funds' performance over short time horizons. They applied the same bootstrap methodology as in Kosowski et al. (2006) and found that top performers show signs of stock-picking skill and bottom performers a sign of lacking it. However, the funds' abnormal performance persists for up to only one year. When evaluating the funds on an aggregate level, Kosowski et al. (2006) concluded the aggregate fund underperforms compared to the relative benchmark.

There have also been several master theses written in Norway on the subject of active mutual fund performance. For instance, Utseth and Sandvik (2015), Mjøs (2018), Aasen and Bødal (2019), and Blørstad and Bakkejord (2017). All four studies report aggregate fund underperformance and none of them seem to find evidence of stock-picking skills among Norwegian fund managers. In addition, three studies concurred on the worst performers lacking skill, whereas Mjøs (2018) only discovered weak evidence of insufficient stock-picking skills among the worst fund managers.

Given the papers discussed so far in this thesis, consensus on the subject of active fund management is yet to be made. We have research concluding in no abnormal fund return, and we have research concluding in abnormal fund return in top performers, bottom performers, and both. The results as a whole are, however, skewed negatively. Most reviewed studies in this section lean towards the conclusion of general underperformance among actively managed funds. In large samples of funds, this will always happen. Some funds will perform worse, and some funds will perform better. What is essential is to figure out the cause of it. Are the top funds overperforming because of luck, or is it due to the fund manager's superior stock-picking skills? On the other hand, are the bottom funds underperforming because of misfortune, or do the fund managers of these funds lack sufficient skill to deliver significant alpha?

3. Theory

In the following section, I will put forward the relevant theory for the research conducted. This theory includes the efficient market hypothesis (EMH), the CAPM, the single-factor model, the Fama-French three-factor model, and the Carhart four-factor model. Lastly, the bootstrap procedure will be presented. The theory section aims to enlighten the theoretical elements of the bootstrap procedure and explain the principles it is built on. Further explanation on how the bootstrap procedure is used in this exact thesis is described in the methodology section.

3.1 The efficient market hypothesis

The efficient market hypothesis, first introduced by Fama (1965), states that beating the market is impossible because stocks are already accurately priced. Here he explains the changes in stock prices by using the "random walk model", and it is concluded that one cannot predict changes in stock prices. This leads to the inference that the best prediction of the future stock price is today's stock price because if the markets are efficient, all stock prices should reflect all available information. Therefore, the EMH states that all successful attempts to beat the market are a result of luck rather than skill. Thus, if the hypothesis is true and the asset reflects all available market information, it is theoretically impossible to make excess profits through investing over a more extended period. The EMH comes into question when one compares active versus passive investing since the hypothesis is often supported by those convinced that passive investing is the better strategy.

Fama (1970) introduced the three forms of market efficiency were: weak, semi-strong, and strong efficiency. *Weak market efficiency* suggests that today's stock prices reflect historical pricing and other financial data (trading volume, short percentage, etc.). The weak form also discounts technical analysis but leaves open the possibility that superior fundamental analysis might outperform the market. *Semi-strong market efficiency* dismisses fundamental analysis as a way to beat the market by assuming that all public information is already calculated into a stock's price. *Strong market efficiency* states that all public and private information in a market is reflected in a stock price. This includes all publicly available information, even insider information. Data not yet available to investors would already be calculated into the current stock price in this form of market efficiency.

There are certain shortcomings of the EMH. *Firstly*, investors do not always think alike and interpret information differently. *Secondly*, even if we would like the stock market to be instantly corrected by changes in the market, delays in stock reactions do happen, however varying in delay time. Early investors can, therefore, sometimes take advantage of this. Thirdly, prices can be affected by human error and irrational decisions. *Lastly*, investors have previously proven that they can earn a profit on anomalies in the market.

The strongest addition to support active fund management is the ”Grossman-Stiglitz paradox”, introduced by Grossman and Stiglitz (1980). It revolves around the redundant roles of financial institutions in an efficient market. Because if all stock prices at all times reflect all available information in the market, there is no longer a demand for the information stock prices are based on. With no profit to be gained by gathering information, there would be little reason for analytics and actively managed funds to exist. The paradox is that the amount of analytics and actively managed funds, whose job is to collect information for conducting valuable trades, is so high. Looking at this from a different perspective where we have no institutions conducting market analyses, one will most likely miss some information on various companies. The possibility then of gaining excess profit by conducting these analyses is likely to be present again. What is most likely to happen in this world is that an increasing amount of participants will want a piece of this cake until the marginal profit equals the marginal cost of collecting such information. The tremendous amount of competition will lead to most participants breaking even, some participants gaining profit while others are losing profit.

3.2 Factor models

Different factor models can be employed to evaluate the performance of fund managers. These models aim to explain the excess return through various risk factors. The performance measure used to assess the fund managers in this thesis is Jensen's alpha. In the different factor models explained in this thesis, the intercept (alpha) is calculated using a time series regression. This alpha (α) represents the risk-adjusted return that is not explained by the specific model's other variables (risk factors). The alpha is therefore attributed to the stock-picking skill of each fund manager. The alpha is also risk-adjusted, which is optimal when comparing funds' performance against each other and the benchmark index.

3.2.1 CAPM

The Capital Asset Pricing Model (CAPM) was developed by Jack Treynor (1962), William Sharpe (1964), John Lintner (1965), and Jan Mossin (1966), building on the former work of Harry Markowitz (1952). The CAPM describes the relationship between expected return and systematic risk (market risk) and aims to calculate the expected return in a perfect market. It is given by

$$E(r_i) = r_f + \beta_i(E(r_m) - r_f), \tag{3.1}$$

where $E(r_i)$ is the expected return and is calculated by taking a risk-free rate of return r_f and adding the stock's sensitivity regarding the market portfolio, β_i, multiplied by the market premium, $(E(r_m) - r_f)$,

3.2.2 Jensen single-factor model

The single factor model by Jensen (1968) is based on CAPM, making it possible to use the CAPM model on historic data and not only for assessing the expected return of an asset. The single-factor model also explains the relationship between risk and return for asset *i* based on its exposure to the market. However, Jensen altered the CAPM model by adding the extra constant of alpha. By adding this constant, the regression equation no longer needs to pass through origo, and the intercept (alpha) can deviate from CAPM and exhibit positive or negative alpha values. Jensen's alpha represents the asset's expected return in a neutral market $\left(r_m - r_f = 0\right)$, where a positive alpha indicates abnormal return above a given benchmark index and a negative alpha indicates abnormal return below a given benchmark index. The measuring of alpha is risk-adjusted as the variance of $\beta(r_{M,t} - r_{f,t})$ and $e_{i,t}$ explanins respectively the systematic market risk and the nonsystematic specific risk. In context with the EMH in section 3.1, in a perfectly efficient market the alpha would be equal to zero. Jensen's single-factor model is given by

$$r_{i,t} = \alpha_i + \beta_i\left(r_{m,t} - r_{f,t}\right) + \varepsilon_{i,t}, \tag{3.2}$$

where $r_{i,t}$ is the excess return of asset i, α_i represents the fund's performance, β_i is the market coefficient, $\left(r_{m,t} - r_{f,t}\right)$ is the market risk premium, later represented by MKT, and $\varepsilon_{i,t}$ is the error term representing the unsystematic risk of the asset.

3.2.3 Fama-French three-factor model

During the 1980s and the 1990s, there was a developing consensus that the single-factor model by Jensen (1968) was not sufficiently accurate for explaining the return on an asset (Marc Reinganum (1981) and Breden et al. (1989)). In addition, empirical research by Stattman (1980), Banz (1981), Basu (1983), and Rosenberg et al. (1985) also observed that other factors than market risk had explanation power for the return of an asset. Basing their model on Jensen's single-factor model and the extensive empirical research on it, Fama and French (1993) therefore added two additional risk factors, the size factor (Small Minus Big - SMB) and the value factor (High Minus Low - HML).

To make their factors, Fama and French (1993) split companies listed on NYSE, Amex, and NASDAQ into different portfolios based on market capitalization, respectively small (S) and big (B). Further, the companies are divided into three groups based on their book-to-market value, high (H), medium (M), and low (L). This process was repeated every year from 1963-1993. The six portfolios SH, SM, SL, BH, BM, and BL, create the basis for developing the SMB- and the HML-factor. The formula for the SMB factor is given by

$$SMB = \left(\frac{1}{3}SH + \frac{1}{3}SM + \frac{1}{3}SL\right) - (\frac{1}{3}BH + \frac{1}{3}BM + \frac{1}{3}BL) \tag{3.3}$$

The SMB-factor assumes that companies with a low market value have a different return compared to companies with a high market value. Bauman et al.'s (1998) research shows that small-cap companies create higher returns than big-cap companies over time. The formula for the HML-factor is given by

$$HML = \left(\frac{1}{2}SH + \frac{1}{2}BH\right) - (\frac{1}{2}SL + \frac{1}{2}BL) \tag{3.4}$$

The HML-factor is constructed by taking the average return of companies with a high book-to-market ratio (value stocks) and subtracting the average return of companies with a low book-to-market ratio (growth stocks). For instance, a positive HML-value indicates that companies with a high book-to-market ratio have had higher returns than the companies with a low book-to-market ratio in a given period. The three-factor model of Fama and French is given by

$$R_{i,t} = \alpha_i + \beta_{1_i} MKT_t + \beta_{2_i} SMB_t + \beta_{3_i} HML_t + \varepsilon_{i,t} \tag{3.5}$$

where $R_{i,t}$ is the excess return of asset i, α_i represents the performance of fund *i* and $\varepsilon_{i,t}$ is the error term. The coefficients, β_{1_i}, β_{2_i} and β_{3_i}, denotes the exposure to the risk factors MKT_t, SMB_t and HML_t respectively.

3.2.4 Carhart four-factor model

Carhart (1997) constructed his four-factor model by adding a fourth factor to the Fama French (1993) three-factor model. This new factor was named the momentum factor (PR1YR) and was based on the former work of Jegadeesh and Titman (1993). In their study, Jagadeesh and Titman find that buying stocks that have performed well in the past and selling stocks that have performed poorly in the past generate significant positive returns over the next 3-12 months. In addition, they discovered that part of this abnormal return was lost in the following two years. Based on this research, Carhart (1997) made a one-year delayed momentum indicator by taking a portfolio of the best performing stocks in the past year and subtracting a similar portfolio containing the worst performing stocks in the past year. The Carhart four-factor model is given by

$$R_{i,t} = \alpha_i + \beta_{1_i} MKT_t + \beta_{2_i} SMB_t + \beta_{3_i} HML_t + \beta_{4_i} PR1YR_t + \varepsilon_{i,t} \tag{3.6}$$

where $R_{i,t}$ is the excess return of asset i, $\varepsilon_{i,t}$ is the error term and the beta coefficients β_{1_i}, β_{2_i}, β_{3_i} and β_{4_i}, denotes the exposure to the risk factors MKT_t, SMB_t and HML_t and $PR1YR_t$ respectively. The coefficient α_i tells us how well the fund performs compared to the model's prediction.

The Carhart (1997) four-factor model will be the primary performance model of this thesis. However, throughout the study, all models will be applied and compared to illustrate each factor's importance for accurately predicting a fund's performance.

3.3 Non-normality and bootstrap

It is fair to say that a positive alpha will be a result of either skill or luck, whereas a negative alpha will be a result of either a lack of skill or misfortune. Therefore, to distinguish between lucky and skilled fund managers and between unskilled and unlucky fund managers in this thesis, a bootstrap methodology similar to Kosowski et al. (2006) is implemented. The implementation of the methodology will be explained in section 4.7.

The previously explained models focus on each actively managed mutual fund individually. When using these models, my inference is based solely on the estimated alpha value and the belonging t-statistic. Standard OLS inference is based on the presumption of normally distributed residuals, and when working with mutual fund data, this presumption is not always fulfilled. The advantage of implementing a bootstrap procedure in the evaluation of ranked funds' alphas and t-statistics is that it is not dependent on the presumption of a normal distribution as the bootstrap procedure will generate its own distribution. Kosowski et al. (2006) pointed out three main reasons why the condition of normally distributed residuals will often not be fulfilled when analyzing mutual fund alphas. The first reason is that stocks' returns can vary significantly. The central limit theorem states that an equally weighted portfolio of non-normally distributed stocks will approach a normal distribution. But because fund managers tend to not invest equally in all stocks in their portfolio, this normality is often not reached. The second reason for non-normality in funds' returns is that different stocks have different levels of autocorrelation and heteroskedastic variance. Thirdly, mutual fund managers often apply dynamic strategies involving adjustments to their level of risk in response to the changes in risk in the overall market or as a response to their performance compared to similar funds. These properties may affect the sample and possibly attribute to non-normalities in mutual fund alphas, making normality a poor assumption for the typical fund. In our dataset, the observations on kurtosis and skewness increase further from the center you get. Using the Carhart (1997) four-factor model to regress and the Jarque-Bera test (Jarque & Bera, 1980), the normality of sampled residuals is rejected for 57.94 % of the mutual funds in our sample, while the normality of mutual fund returns is rejected for 74.77 % of our sample. Both are rejected at the 5 % significance level.

The bootstrap procedure employs a cross-section of estimated alpha values, and when using such a cross-section, there is an increased number of reasons for non-normality to occur. This is because even though the funds individually have normally distributed residuals, the cross-section of alpha can create a non-normal distribution due to each fund's different risk exposure. Funds exposed to higher risk have a higher probability of being located in the tails of the alpha distribution, and funds less exposed to risk have a higher chance of being located somewhere in the middle of the alpha distribution. This means that the distribution of alpha will vary depending on each fund's risk exposure, and due to this, it is possible to end up with thicker or thinner tails than with a normal distribution. However, if you look at the t-statistic of alpha instead of alphas, the problem of non-normality due to funds' risk exposure disappears. The t-statistic is normalized by the standard deviation of returns, thus making the t-statistic risk-adjusted. It can, however, be non-normality in the distribution of t-statistics if individual funds have non-normally distributed residuals.

An assumption of normality is considered a poor approach in this thesis, as the cross-sectional distribution of mutual funds consists of various individual fund distributions. The bootstrap procedure is therefore preferred when analyzing the significance of Norwegian mutual funds' alpha value. Kosowski et al. (2006) state that a bootstrap is especially important for correct inference when analyzing a dataset with relatively few funds or a low amount of observations. Compared to some of the studies in the literature review, I consider both the number of funds (107) and the number of observations (smallest being 12 observations) as fairly low. Therefore, the bootstrap is deemed essential to the analysis of Norwegian mutual fund performance, especially when it comes to distinguishing skill from luck.

4. Methodology

The methodology section aims to explain the approach of the thesis. Mainly, I will elaborate on the selection of funds and choice of benchmark as well as the return, excess return, and alpha calculations. Furthermore, I will explain the use of regression analysis and present the implementation of the bootstrap procedure and how the method is used to distinguish between luck and skill, which is the primary goal of the thesis.

4.1 Choice of funds

The choice of funds is vital to maintain consistent results, and in the end, consistency is what we are looking for when we compare several funds with one benchmark. This thesis builds on a dataset consisting of 107 actively managed Norwegian mutual funds containing both surviving and non-surviving funds. The fund data stretches from January 1987 to December 2019. All funds pursuing neutral investment strategies are omitted, and each fund has a minimum of 80 % domestic equities. There are no conditions regarding fund size, but it is assumed that in cases of merged funds, the money is invested in the acquiring fund (Elton et al., 1996b). The period is selected based on available information on funds and benchmark index. I followed Ødegaard's (2019b) arguments to construct the risk-free rate of return. Based on his data, which had a period from 1980 to 1986 with less accurate estimates of the risk-free rate of return, I decided to start the period in 1987. Like the restrictions on fund nationality and investment strategy, the decision to only include Norwegian funds that invest their majority of assets in the Norwegian equity market is made to protect the research's consistency. The risk exposure likely varies from one country to another, and doing this, along with omitting funds with neutral investment strategies, enables the use of one single benchmark index.

4.2 Choice of benchmark

To measure a fund's performance, we need a comparable benchmark index to represent the market returns. There are several different Norwegian indexes to choose from, but choosing the right one is crucial for the validity of our research. The majority of active Norwegian mutual funds use the Oslo Stock Exchange Mutual Funds Index (OSEFX). The OSEFX is a capped version of the OSEBX (Oslo Stock Exchange Benchmark Index), which capping rules comply with Undertakings for Collective Investments in Transferable Securities (UCITS) directives for regulating mutual funds investments (Euronext.com, 2021). The OSEFX would be a suitable benchmark, but as it originated first in 1995, we cannot use it as a benchmark between 1987 and 1995. To get as consistent results as possible, using only one index for the whole period is preferred. Therefore, the Oslo Stock Exchange All-Shares Index (OSEAX) is the next best choice for the funds' benchmark. The OSEAX consists of all shares listed on the Oslo Stock exchange and is adjusted for corporate actions and dividend payments. According to Sørensen (2009), however, since the OSEAX consists of some very illiquid stocks, replicating this portfolio would mean high transaction costs. Therefore, using OSEAX as the benchmark might be an unfair index as the factors in the index are estimated before transaction costs, while the returns for the funds are after transaction costs. This difference in transaction cost is worth taking into account when assessing the funds' performances.

4.3 Risk-free rate of return

The risk-free interest rate is constructed following the arguments of Ødegaard (2019b). The starting point has been limited to 1987 since the interest rate data between 1983 and 1986 is considered chaotic. Using the one-month Norwegian Interbank Offered Rate (NIBOR) as the interest rate proxy, the risk-free interest rate is calculated as

$$r_{f,t} = (1 + NIBOR)^{\frac{1}{2}} - 1. \tag{4.1}$$

The plot of the monthly overnight NIBOR rate for the entire sample period from 1987 to 2019 is reported in Appendix A.

4.4 Calculation of returns

The historical fund data is obtained from the TITLON database. The daily NAV-listings (Net Asset Value) are downloaded and converted to monthly listings using the last listing from each month. The monthly return for fund *i* on time *t* is given by

$$r_{i,t} = \frac{NAV_{i,t} - NAV_{i,t-1}}{NAV_{i,t-1}} \tag{4.2}$$

where $r_{i,t}$ is monthly return, $NAV_{i,t}$ is the net asset value for fund *i* at the last listing in month *t*, and $NAV_{i,t-1}$ is the net asset value of the last listing the previous month. The NAV is calculated by dividing the number of stocks in the fund by the fund's total value. The NAV is subtracted management fees, but it does not account for the cost of buying or selling a fund. Using the monthly return in equation 4.2, we can get the excess return of fund *i* by subtracting the risk-free monthly rate of return.

$$R_{i,t} = r_{i,t} - r_{f,t} \tag{4.3}$$

4.5 The performance measure alpha

The excess return that has been calculated till now is the excess return over the risk-free rate. To assess the funds' performance, one needs to compare the funds to a relevant benchmark index, in our case, the OSEAX. However, since the risk level in different funds can be substantial, the funds are measured using a risk-adjusted return. That is why, in this thesis, alpha (α) is used as the measure of risk-adjusted excess return. The alpha is calculated as a constant in the factor models and represents the average monthly risk-adjusted excess return beyond the models' prediction. A true alpha of zero will mean that the fund performs well enough to justify its management cost, but not much else.

In the factor models, the systematic risk exposure of a fund is shown through the factor coefficients, while the unsystematic risk is represented by the error term (ε_i). The estimated alpha ($\hat{\alpha}$) accounts for relevant risk, making it risk-adjusted and a just performance measure to compare the different funds' performance. Alpha will vary using the different factor models due to the change in systemic risk when changing the number of risk factors.

4.6 Regression analysis

In the first part of the analysis of actively managed Norwegian funds, I compare the single-factor model, Fama-French three-factor model, and the Carhart four-factor model using regression analysis. Regression analysis is used to describe the relationship between the dependent variable, alpha, and the independent variables, beta (Braut & Dahlum, 2018). The ordinary least squares (OLS) method is used to estimate the variables using the observed data. This method minimizes the sum of squares between the observed dependent variable and the independent variables. From the OLS method, you also get the model's explanation power, R^2, which explains how much of the variance is explained by the dependent and independent variables. R^2 will remain unchanged or increase when more variables are added to a model. To distinguish between the different models' explanation power, adjusted R^2 (R^2_{adj}) is used instead. Here, if a new variable is added, without contributing explanation power to the model, R^2_{adj} will decrease.

First, I perform a regression using an equally weighted portfolio (EWP) consisting of all funds in the data sample. By doing this, I can analyze the funds' performance on an aggregate level to determine if the average Norwegian fund can defend its costs. The size of each fund has not been taken into account because it is not possible to obtain the value of assets under management for discontinued funds. The regression estimates the alpha and the exposure to the different risk factors. This is done for all three models, and the results are presented along with its corresponding t-statistic, p-value and R^2_{adj} in Table 3. Next, I perform a regression for each fund individually using the Carhart (1997) four-factor model from equation 3.7. Using the same model for the bootstrap procedure, I will compare the estimated and bootstrapped alpha and present the findings in section 6. The implementation of the bootstrap procedure is explained in the next section.

4.7 Implementing the Bootstrap procedure

To be able to contribute the performance of each fund to the result of either luck or skill, I follow the bootstrap procedure of Kosowski et al. (2006), under the condition of no true performance in individual funds ($\alpha_i = 0$). The first step of this procedure is to estimate alphas, factor loadings, and residuals by using the OLS regression explained in the previous section. This is done using the time series of monthly excess return (net returns minus risk-free return) for fund *i* with the Carhart four-factor model presented in equation 3.7. We recap

$$R_{i,t} = \hat{\alpha}_i + \hat{\beta}_{1_i} MKT_t + \hat{\beta}_{2_i} SMB_t + \hat{\beta}_{3_i} HML_t + \hat{\beta}_{4_i} PR1YR_t + \varepsilon_{i,t}. \tag{4.4}$$

Before the bootstrap simulation, for each fund, I reserve the coefficient estimates for alpha and risk factors ($\hat{\alpha}_i, \hat{\beta}_{1_i}, \hat{\beta}_{2_i}, \hat{\beta}_{3_i}, \hat{\beta}_{4_i}$) and t-statistic of alpha ($\hat{t}_{\hat{\alpha}}$). In addition, I save the residuals $\hat{\varepsilon}_{i,t}$, where t= $T_{i0},\dots, T_{i1}$. T_{i0} and T_{i1} are the dates of the first and last month for fund *i*, respectively. Next, from each fund *i*, I draw a random sample with replacement from the residuals saved from the OLS regression. This will construct a pseudo-monthly time series of resampled residuals that will have the same length for all funds because of the resampling. The length is given by $\hat{\varepsilon}^b_{i,t_\varepsilon}, t_\varepsilon = S^b_{T_{i0},\dots,T_{i1}}$, where S represents the sampled residual of bootstrap number b (b=1,…, 10 000) and T defines the start and endpoint of the time series. Every $S^{b}_{T_{i0},\ldots,T_{i1}}$ is randomly sampled from $T_{i0},\ldots,T_{i1}$ such that the original sample of residuals of each fund gets reorganized. Estimated factor coefficients remain unaltered and maintain the same chronological order in the newly constructed dataset. By using the saved factor coefficients from the OLS regression and the new time series of bootstrapped residuals, I construct a new time series of pseudo-monthly excess return for fund *i* under the null hypothesis of no true performance in individual funds ($\alpha_i = 0$). By adding the restriction of alpha equal to zero, the null hypothesis states that no funds perform any better or worse than expected. Therefore, I estimate

$$R^{b}_{i,t} = 0 + \hat{\beta}_{1_i} MKT_t + \hat{\beta}_{2_i} SMB_t + \hat{\beta}_{3_i} HML_t + \hat{\beta}_{4_i} PR1YR_t + \hat{\varepsilon}^{b}_{i,t_\varepsilon} \qquad (4.5)$$

In the regression of the new Carhart four-factor model given in 4.5, positive or negative alphas (and t-statistic of alpha) will emerge if an abnormal number of positive or negative residuals are drawn from a bootstrap sample *b*. This procedure is repeated for all funds *i*= 1,…, *N*, which results in a bootstrapped alpha for every fund. This procedure is then repeated 10 000 times to construct the distribution of the cross-section of bootstrapped alphas and t-statistic of alpha. The cross-section of alpha-values ($\hat{\alpha}^{b}_{i}, i = 1,2,\ldots,N$) and the t-statistic of alpha ($\hat{t}^{b}_{\hat{\alpha}i}, i = 1,2,\ldots,N$) are then ranked from the highest to the lowest value for each bootstrap *b*. This way, we achieve a distribution of alphas ($\hat{\alpha}^{b}_{i}$) and t-statistic of alpha ($\hat{t}^{b}_{\widehat{\alpha_i}}$) that is a result purely of sampling variation. The distributions of alpha and t-statistic of alpha are gathered into two Nx10 000 matrices, where N=107. These distributions are then compared with the observed alpha and t-statistic from the Carhart four-factor model to determine if good or bad fund performances can be attributed to skill or incompetence, respectively. The chosen hypothesis is determined by the sign of the observed t-statistic of alpha. If the observed t-statistic of alpha is positive, I test the null hypothesis of alpha equal to zero (fund managers are lucky) against the alternative hypothesis of alpha higher than zero (fund managers are skilled) ($H^{+}_{0}: \alpha_i = 0$, $H^{+}_{A}: \alpha_i > 0$). If the t-statistic of alpha is negative, I test the null hypothesis of alpha equal to zero (fund managers are unlucky) against the alternative hypothesis of alpha lower than zero (fund managers lack skill) ($H^{-}_{0}: \alpha_i = 0,\ H^{-}_{A}: \alpha_i < 0$). For example, for the top-performing fund, we would compare the bootstrapped distribution of alpha with the estimated alpha to determine if the fund manager of this fund is lucky or skilled. If the bootstrap procedure generates a sufficient amount $\hat{\alpha}^{b_i}_{top}$ that is lower than the observed alpha, we can conclude that the highest observed alpha is not a result of luck, but instead that the manager of this specific fund has stock-picking skills (Kosowski et al., 2006). In this thesis, the sufficient amount is decided by the computed p-value, whereas the significance level is set at 5 %.

In the empirical analysis, I will consider both alpha and t-statistic of alpha. But, like Kosowski et al. (2006), I will primarily use the t-statistic of alpha. As it "controls for differences in risk-taking across funds" (Kosowski et al., (2006), p.2555), the t-statistic is considered having the superior statistical ability as a sorting term when comparing funds under the null hypothesis of zero true performance, $\alpha = 0$ (Busse et al., 2010; Fama & French, 2010; Kosowski et al., 2006). Our dataset of mutual funds consists of funds with varying lifespans. Mutual funds with a short lifespan and a high-risk characterization will have a greater variance in their estimated alpha distribution and generate outliers in the cross-section. By ranking the funds on t-statistic of alpha instead of alpha when comparing with the equivalent percentiles from the bootstrap simulation, the risk level of each fund is considered. Following these arguments, the distribution of t-statistics of alpha, rather than alpha, will be favored when comparing different funds' performances to the benchmark index. Due to limited computation power, the number of resamples in the bootstrap is set to R=10 000. When comparing the bootstrap results to a resample count of R=1000, they do not significantly change. Therefore, I consider the number of resamples sufficient for my thesis. All 107 funds are included in the bootstrap simulation. The bootstrapped results are shown in section 6.3.

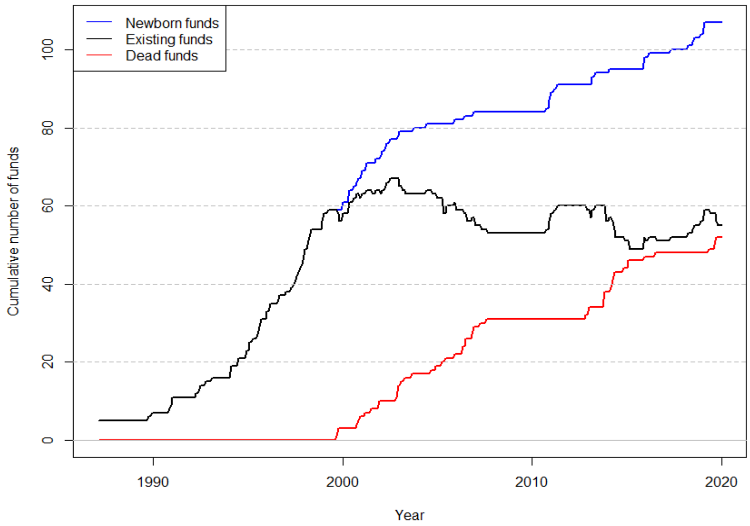
5. Data

This section will present the details of the collection process of the data used to evaluate the active Norwegian mutual funds in this thesis. I will first explain the gathering procedure for the historical data on sample mutual funds, risk factors, interest rate, and benchmark. Then, I will elaborate on the potential biases of this research. The reasoning for the gathering of the specific data is explained previously in section 4.

The dataset comprises 107 active Norwegian mutual funds sampled from the Oslo stock exchange between 1987 and 2019. The condition of a minimum of 12 monthly net return observations has been established to ensure reliable results. The accumulated monthly development of active Norwegian mutual funds is shown in Figure 1, with only 5 active funds in January 1987 and 55 active funds in December 2019 (black line). 52 funds have been listed and later closed up in the 33 year sample period, referred to as *Dead funds* (red line) in the graph. The average lifetime of a fund in the dataset is 13.6 years. The plot reports that the number of Norwegian active mutual funds stagnated at the beginning of the 2000s at around 60 funds. Since then, the number of actively managed mutual funds has been relatively consistent, with approximately 50 to 60 funds.

Figure 1 – Accumulated monthly development of active Norwegian mutual funds

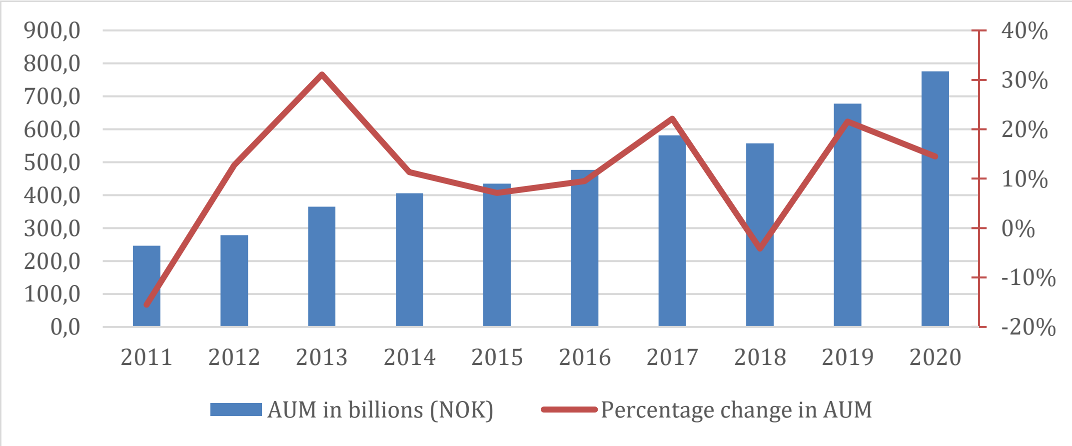
The Newborn funds (blue line) account for the monthly accumulated listing of active Norwegian mutual funds. Existing funds (black line) report the number of active funds at any time. Dead funds (red line) report the monthly accumulated closed funds.



The increase in the number of funds is a sign of high demand. And if the increased demand is not met by additional funds to invest in, the funds' assets under management (AUM) will grow instead. As shown in Figure 2, AUM for Norwegian funds has increased from NOK 246 billion to NOK 775 billion just in the last ten years. Moreover, the growth has been negative in only two instances, 2011 and 2018, with -16 % and -4 %, respectively. (VFF, 2020) Therefore, it is fair to say that the Norwegian mutual fund market has continued its popularity growth in recent years.

Figure 2 – Historical data on assets under management in the Norwegian fund market.

The figure reports the assets under management using the blue columns. The amount can be seen on the left Y-axis of the figure reported in billions of Norwegian kroner. The percent change each year is represented by the red line with the percentage amount on the right Y-axis. The X-axis displays the year.



(VFF, 2020)

5.1 Data collection

The historical fund data used in this thesis has been obtained from the TITLON database. I collected the daily net asset values (NAV) and converted them into monthly returns. The home page of Bernt Arne Ødegaard was used both to get the monthly risk-free return and the monthly listings on the risk factors, SMB, HML, and PR1YR. These factors are estimated by Ødegaard based on empirical data from the Oslo stock exchange.

5.2 Risk factors

To calculate a fund's alpha, I use regression analysis. In the regression analysis, the market factor MKT and the risk factors estimated by Ødegaard (2019a) function as the independent variables. Table 1 compares each factor's annualized mean return, standard deviation, and maximum and minimum return. In addition, I report the correlation coefficient between each risk factor. Of the three risk factors, the momentum factor PR1YR produces the highest mean return with 8.67 %, while the value factor HML produces a mean return of only 2.08 %. The market factor MKT and the size factor SMB produce approximately the same return at 7.09 and 7.85, respectively. All factors have generated positive mean returns. The positive SMB-factor indicates that small companies produced higher returns than big companies, while the positive HML-factor indicates that value stocks generated a higher return than growth stocks. Ranging from 14.16 % to 16.31 %, the standard deviations are pretty similar for SMB, HML, and PR1YR. The standard deviation of the MKT distinguishes itself from the others, having a much higher standard deviation of 20.74 %. SMB reports the highest maximum return of 22.14 %, while the MKT reports the lowest minimum return of -28.69 %. Reading the correlation table, there seems to be a relatively low correlation between each factor, except for the negative correlation between MKT and SMB of -0.45. This negative correlation means that big companies do better than small companies when the market goes up, and vice versa.

Table 1 – Descriptive statistics for factor returns

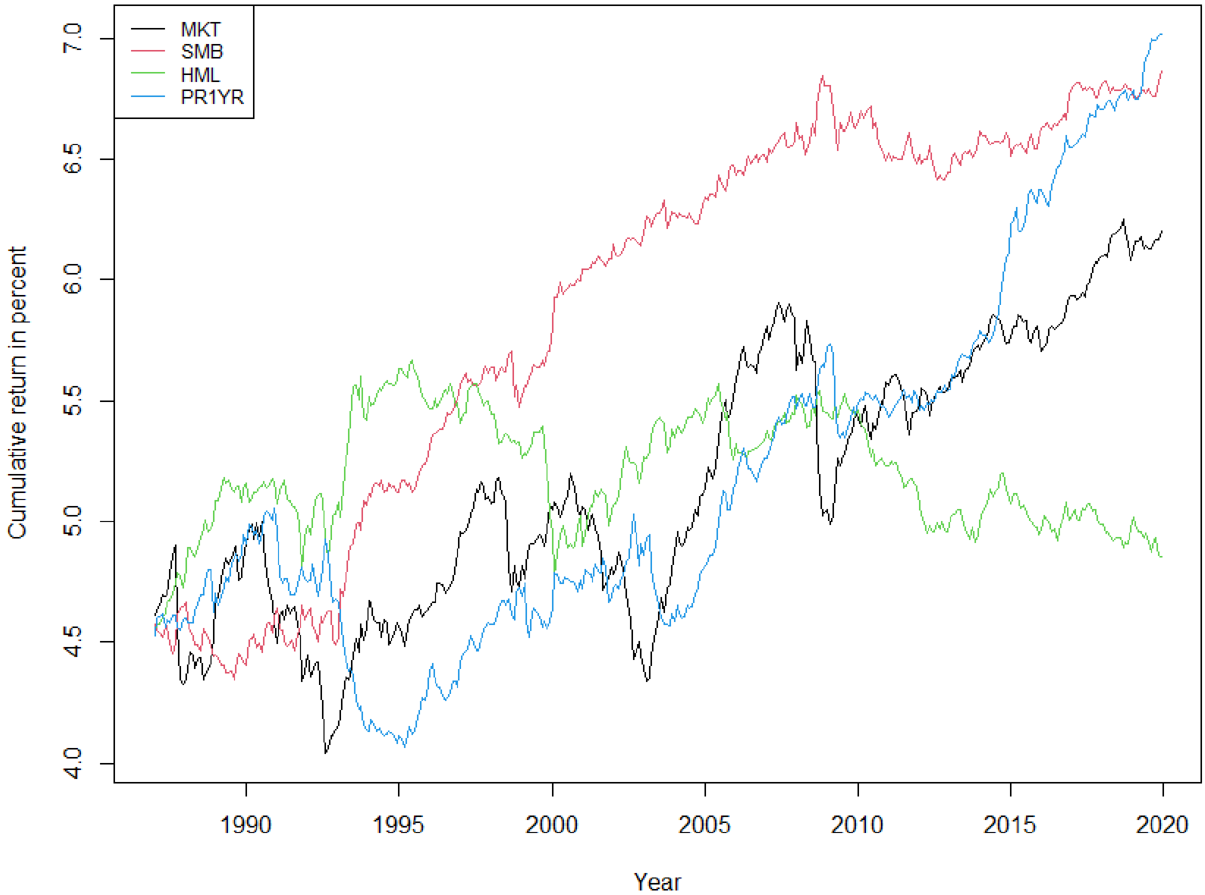
The table reports annualized mean return, standard deviation, and the maximum and minimum return for each factor in 1987-2019. At the bottom, you can see the risk factor correlation coefficients.

Factor statistics	MKT	SMB	HML	PR1YR
Mean return	7.09	7.85	2.08	8.67
Standard Deviation	20.74	14.16	16.18	16.31
Maximum return	16.51	22.14	14.66	15.43
Minimum return	-28.69	-17.08	-16.65	-16.78
Factor correlation coefficients				
MKT	1.00			
SMB	-0.45	1.00		
HML	0.05	-0.14	1.00	
PR1YR	-0.16	0.11	-0.12	1.00

Figure 3 reports the cumulative returns of the factor loadings in logarithmic form for the entire sample period. As you can see from the reported standard deviation in Table 1, the market factor is highly volatile. This volatility can also be seen in the plot, especially in the period before 2010. The SMB-factor provides the lowest standard deviation and increases steadily from 1993 to 2010, where it stabilizes. The HML-factor has the lowest mean return of all the risk factors. Reporting high volatility between the mid-1990s until 2000, it decreases in cumulative return after approximately 2005. The PR1YR-factor reports an all-time low in the mid-1990s before steadily growing, reaching the highest cumulative return of all risk factors in 2019. The cumulative return of each risk factor can be seen in the time series plot in Appendix B.

Figure 3 – Cumulative return loadings of risk factors

Time series plot reporting the cumulative factor returns in the Carhart four-factor model from 1987-2019. The different impacts of the risk factors are given in the logarithmic scale with year on the x-axis.



5.3 Potential biases

When conducting statistical analysis, potential biases will arise. Common biases when running simulations are *sample selection bias*, *survivorship bias*, *time period bias*, and *look ahead bias*. Sample selection bias is a type of bias that can occur if the data you choose to use is non-random or if you decide to exclude parts of your sample from the study. In previous studies, the most prevalent sample selection bias has been the survivorship bias. This is a type of sample selection bias that occurs when non-surviving funds are removed from the data sample (Brown et al., 1992). Brown et al. (1992) was one of the first to research the difference between surviving and non-surviving funds and discovered that by not including the delisted funds, the relationship between return and volatility becomes positively skewed. In a later paper, Brown and

Goetzmann (1995) found that the biggest reasons for funds being liquidated are poor track record, size, age, and the fund's expense ratio, track record being the most important. In addition, carpenter and Lynch (1999) found that liquidated funds suffer from multiple-year underperformance. Naturally then, funds that persistently perform and yield a high return tend to survive. Therefore, excluding dead funds lead to the sample's average return being positively biased. To counteract any survivorship bias in this thesis, both survived and non-survived funds are included in the analysis. The relationship between the number of survived and non-survived funds can be seen in Figure 1 at the start of this chapter.

In Table 2, you can see the descriptive statistics underlining the importance of including non-survived funds. The benchmark index and the equally weighted portfolio (EWP) of all sampled funds yield relatively similar returns of 12.38 % and 12.60 %, respectively. Most significant, is the difference between living and dead funds with a mean return of 13.71 % and 10.92 %, respectively. The standard deviation of all EWPs is fairly similar, and so is the maximum and minimum return. When looking at the two last statistics, it is interesting to see the EWPs of funds produce such similar results, with a kurtosis of 2.04 to 2.12 and a negative skewness of -0.79 to -0.81. It seems that even though they produce significantly different mean returns, they all have roughly the same distribution shape. The OSEAX produces a bit higher estimates with a kurtosis of 2.84 and a negative skewness of -0.99.

Table 2 – Descriptive statistics for benchmark and funds

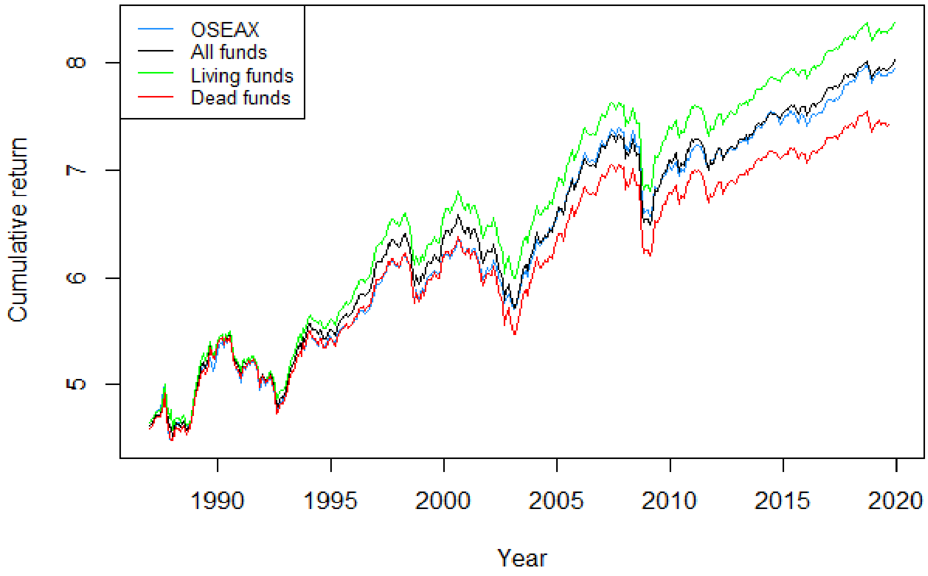
The table reports various descriptive statistics for equally weighted portfolios consisting of OSEAX, all funds in the sample, all existing funds (living funds), and the non-surviving funds (dead funds). Columns 1 to 6 report the mean return, standard deviation, maximum return, minimum return, kurtosis, and skewness. All numbers are in percent and reported for the period January 1987 – December 2019.

	Mean return	Standard deviation	Max return	Min return	Kurtosis	Skewness
OSEAX	12.38	20.62	17.45	-27.42	2.84	-0.99
All funds	12.60	20.63	17.55	-25.28	2.11	-0.81
Living funds	13.71	20.81	18.65	-25.39	2.04	-0.79
Dead funds	10.92	20.97	18.14	-25.09	2.12	-0.79

Figure 4 displays the cumulative return of all EWPs in Table 2. Studying the figure, the surviving funds yield consistently higher returns than the dead funds, and the OSEAX and EWP of all funds closely follow each other. Thus, from the data, we can confidently conclude that excluding liquidated funds will increase the historical yields of our sample and impose potential survivorship bias. Therefore, liquidated funds can not be omitted.

Figure 4 – Cumulative return for benchmark and funds

The graphs depict the cumulative return of the market (OSEAX), all funds, survived funds, and dead funds in the period of January 1987 – December 2019. The cumulative return is given in logarithmic form on the Y-axis, and time is given on the X-axis.



The other biases I consider relevant to my thesis are the *time period bias* and the *look-ahead bias*. Time period bias may occur when selecting observations that only cover a specific time period. To avoid this, I try to use observations spanning over a wide time range as this will maintain the study's rigor. Some funds have few observations due to their short lifespan. This is something to be aware of, especially when analyzing funds individually on a parametric level. The look-ahead bias was introduced by Carpenter and Lynch (1999) and may occur when using information that was not available at the time of investing. We know more now looking back than we did initially. Therefore, to avoid look ahead bias when conducting analysis on historical data, one must be careful to judge former performances on a fair basis and also to use the correct time-specific information. This is vital for the thesis to reach a truly significant conclusion.

6. Empirical results

In this section, I will present the findings of the empirical analysis of the Norwegian mutual fund performance. The main focus of the analysis will be on the Carhart (1997) four-factor model, although the other models are included for comparison. First, I will look at the funds' performance on an aggregate level using Jensen's (1968) single-factor model, Fama and French's (1993) three-factor model, and Carhart's (1997) four-factor model. Afterward, I will evaluate individual funds and their bootstrapped results to determine the existence of skilled or unskilled mutual fund managers in our sample.

6.1 Aggregate fund performance

By using an equally weighted portfolio of all 107 actively managed funds in the regression analysis, we can compare the funds' performance on an aggregate level using the three different factor models. Under the null of true alpha equal to zero, we focus on whether the average fund can yield a positive alpha and how the different factor loadings affect the results.

In Table 3, you can see the results of the regression. The CAPM generated an alpha of 0.50 %. The Fama-French three-factor model generated an alpha of -0.38 %, while Carhart's four-factor model generated an alpha of 0.04 %. Looking at the p-values, however, none of these alphas are statistically significant. This means that we cannot reject the null hypothesis ($H_0: \alpha = 0$), that the funds on an aggregate level produce any abnormal return, negative or positive, using any of the different factor models. All independent variables are statistically significant, with only the momentum factor having a higher p-value than one percent. When adding the size- and value-factor of the Fama-French three-factor model, the alpha is negatively affected, while the Momentum factor of Carhart's four-factor model shifts the alpha up. At the same time, the market factor is the most contributing factor in both models by quite a lot. The adjusted R^2 is reasonably high for all three models. The market factor explains 92 % of the variance of alpha in the single-factor model. 93 % of the variance of alpha in the Fama-French three-factor model and Carhart four-factor model is explained by their respective risk factors.

Table 3 – Alpha and factor loadings for EWPs

The table displays the alpha, factor loadings, and adjusted R^2 for the equally weighted portfolio based on the entire sample of Norwegian funds over the period 1987-2019. The calculations have been made for the CAPM, the Fama-French three-factor model, and Carhart's four-factor model. Alphas are annualized in percent.

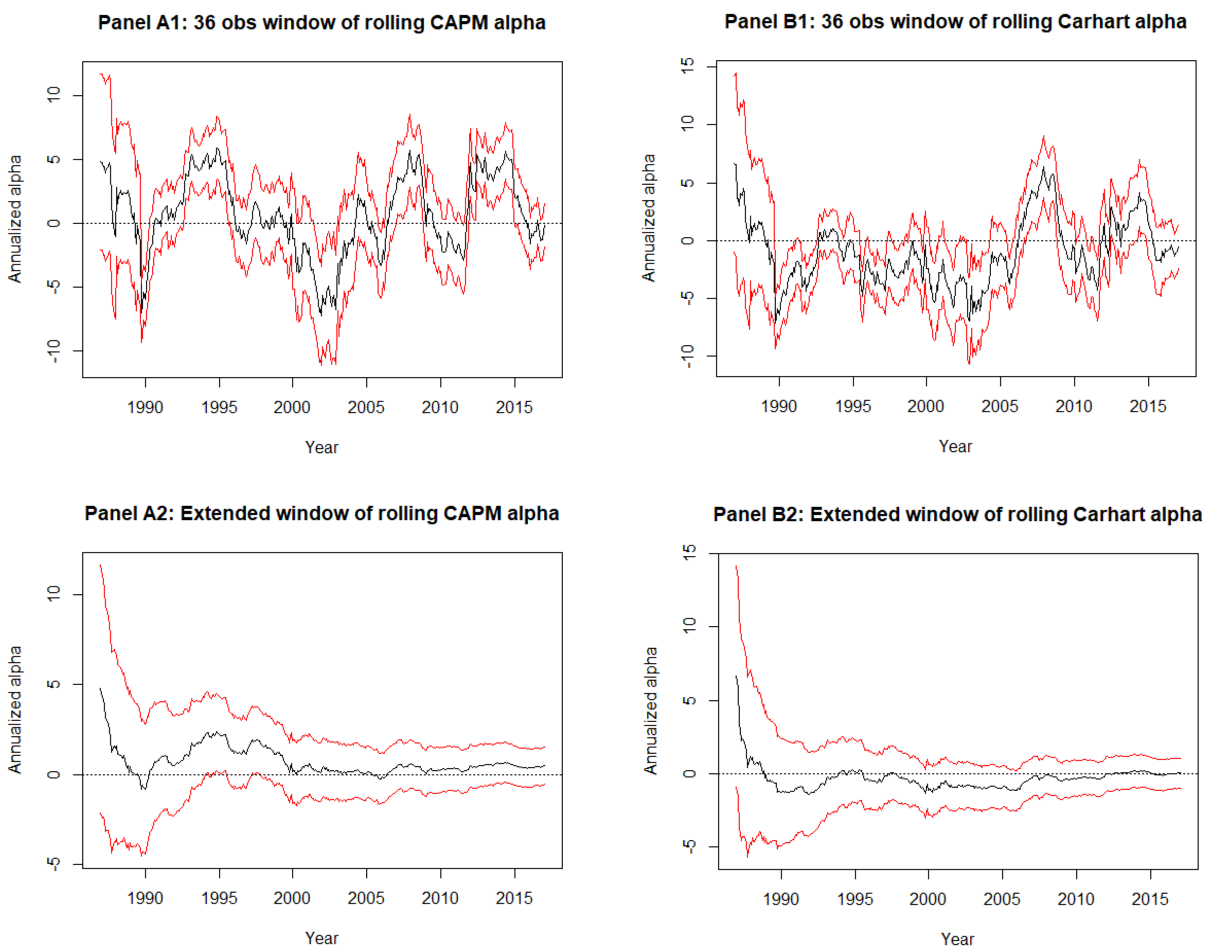
Model		α	β_{MKT}	β_{SMB}	β_{HML}	β_{PR1YR}	R^2_{adj}
CAPM	α- and β-loadings	0,50	0,96				0,9193
	t-stat	0,49	67,10				
	p-value	0,63	0,00				
FF	α- and β-loadings	-0,38	0,99	0,10	-0,06		0,9255
	t-stat	-0,37	64,54	4,34	-3,39		
	p-value	0,71	0,00	0,00	0,00		
Carhart	α- and β-loadings	0,04	0,99	0,10	-0,07	-0,04	0,9265
	t-stat	0,03	64,13	4,43	-3,66	-2,48	
	p-value	0,97	0,00	0,00	0,00	0,01	

Figure 5 displays how the alpha of the equally weighted portfolio has evolved from 1987 through 2019. The monthly alpha observations are analyzed using two different rolling windows as well as comparing the Jensen single-factor model and the Carhart four-factor model. Both windows start at 36 months. The 36 observation rolling window is calculated 1-36, 2-37, …, 361-396, while the extended rolling window is calculated 1-36, 1-37, …, 1-396. Panel A1 and A2 are computed using the Jensen (1968) single-factor model, while panels B1 and B2 are computed using the Carhart (1997) four-factor model. The red lines display the standard error of alpha.

Looking at panels A1 and B1, we have the 36 observation rolling window of alpha calculated using Jensen's single-factor model (CAPM) and Carhart's four-factor model, respectively. We can see that the alpha starts right under the 5 % level for both panels A (CAPM), whereas panel B (Carhart) begins at around 7 %. The Carhart alpha tends to fluctuate less due to the added risk factors, but you can also see that it tends to have lower highs, especially around the years 1994-1995 and 2013-2014. The lows of both panels are, however, relatively similar. It also seems as the Carhart alpha in panel B1 experiences a lower alpha in general compared to panel A1. This is likely due to the added risk factors, which are negative except for the size factor. When we examine the extended windows, this can be seen more clearly. The extended window of the CAPM alpha starts positive but dips under the zero mark around 1990. Following this, it has a positive trend before mostly staying on the positive side of zero. When we compare it to the Carhart alpha in panel B2, we can see that it also had a negative dip around 1990. However, it never seems to recover after this, hovering right under the zero mark before approaching zero in the end. Like we saw in Table 3, the alpha is heavily affected by the market factor. Therefore, we can use historical events like Black Monday in 1987, the Dotcom bubble in 2000, the financial crisis in 2007, and the Chinese stock market crash in 2015 to explain some of the fluctuations in both the CAPM and Carhart alpha.

Figure 5 – Rolling window estimates for alpha

The different panels in the figure report the estimated alpha of the equally weighted portfolio of the sample funds in the period 1987-2019 using two different windows (36 and 396) and two different models (Jensen's CAPM and Carhart's four-factor model). Panel A1 and A2 report the rolling and extended windows, respectively, using the estimated alpha derived from the CAPM. Panel B1 and B2 report the rolling and extended windows, respectively, using the estimated alpha derived from Carhart's four-factor model. The top panels use a rolling window of 36 observations, while the bottom panels use an extended window of 396 observations. The black line reports the alpha, while the red lines report the standard errors of alpha. The alpha estimates are annualized and reported in percent for all figures.



Judging by the rolling windows of Figure 5 and the factor loadings of Table 3, it seems that over the last 30 years, the aggregate fund has had little to no abnormal performance from the benchmark. In other words, it appears the aggregate fund does little but collect management fees and that the average fund manager lacks the skill to beat the benchmark index. However, this does not exclude the possibility that there are good fund managers out there. Or bad ones, for that matter. Evaluating the funds on an individual level will therefore be next.

6.2 Single fund performance

Using Carhart's four-factor model, I evaluate all sample funds individually. What I am looking for is essentially significant positive or negative alpha values. The period is looked on as a whole with the results of the outer funds in focus. Table 4 reports the total number of significant alphas in our sample and the distribution between significant negative and positive alphas. In total, I find 19 significant alphas at the 5 % level and an additional 11 significant alphas at the 10 % level. The funds in our sample exhibit a greater number of significant negative alphas on every significance level, and we also have no significant positive alphas at the 1 % significance level. At the 5 % level of significance, there were 12 significant negative alphas and 7 significant positive alphas. The "negative versus positive alpha" distribution trend is also present at the 10 % significance level, with 21 out of 30 alphas being significantly negative. All estimated alpha values, as well as the belonging t-statistics for each individual fund, can be seen in Appendix C.

Table 4 – Significant alphas

The table displays the total number of significant alphas and the number of positive and negative alphas in our sample at the 1 %, 5 %, and 10 % significance level. Alphas that are significant on a 1 % level are also counted as significant on the 5 % and 10 % level. The calculation of p-values is based on the alpha and the belonging t-statistic.

Significance level	1 %	5 %	10 %
Significant positive alphas	0	7	9
Significant negative alphas	5	12	21
Total significant alphas	5	19	30

However, even though we have significant alpha values at the 5 % significance level, we cannot confidently say that the fund managers' performance is due to skill or a lack thereof. This is because of the properties of the parametric one-sample t-test, as mentioned in the introduction. Significant alphas can appear due to luck alone. The number of observations for each fund differs, all the way down to only 12 observations. Using the bootstrap methodology of Kosowski et al. (2006) in the next section, I want to distinguish skill from luck and find out if skilled or unskilled fund managers exist in the Norwegian equity market.

6.3 Bootstrap results - Skill versus luck

Statistically, looking at different samples of funds, there will always be some funds performing better or worse than the chosen benchmark. Therefore, this section focuses on distinguishing skill from luck in individual fund performances. For this, I use the bootstrap methodology of Kosowski et al. (2006). Again, we are looking for significant p-values as we previously did, but this time we are looking for them using the bootstrapped results. As stated in section 4.7, the bootstrapped results are estimated under the joint null of zero true performance ($\alpha_i = 0$). This means that every fund that reports a significant bootstrapped alpha can be considered skillful or lacking in skill. To distinguish between skill and luck, we test the following hypotheses for positive and negative t-statistics, respectively:

$$H_0^+ : \alpha_i = 0, \;\; H_A^+ : \alpha_i > 0 \tag{6.1}$$

$$H_0^- : \alpha_i = 0, \;\; H_A^- : \alpha_i < 0 \tag{6.2}$$

Table 5 provides the bootstrapped results and results from the parametric t-test for the top and bottom ten funds. The fund name, alpha, t-statistic of alpha, and the number of observations for each fund are displayed in the table, and the results are sorted by their alpha values. The table is split into two panels, A and B, where panel A contains the top ten performing funds while panel B contains the lowest ten performing funds. Interestingly, none of the top-performing funds had significant bootstrapped p-values. The closest was "Landkreditt Utbytte" with the second-highest alpha and a bootstrapped p-value of 0.11. "FIRST Generator" produced the highest yearly alpha of 10.95 %. This means we cannot reject the null hypothesis of zero abnormal performance ($H_0^+ : \alpha_i = 0$) for any of the top ten funds. For the bottom ten funds, all but one fund obtained a statistically significant p-value ($p < 0.05$). The lowest-performing fund, "Danske Invest Aktiv Formuesf. A", generated a yearly alpha of -19.06 % with a bootstrapped p-value of 0.01. This means we can reject the null hypothesis of zero abnormal performance ($H_0^-: \alpha_i = 0$) for all but one ("Skandia Horisont") of the bottom ten funds. Based on these results, we cannot reject that the high alpha values seen in the top funds are due to luck. And unfortunately for the funds, the worst-performing fund managers seem to lack the sufficient skill to generate positive alpha returns for their investors. The full table of results from each individual fund is provided in Appendix C.

Table 5 – Top and bottom funds ranked on alpha.

The table provides the cross-sectional bootstrapped results of all Norwegian mutual funds in our sample from 1987-2019. Using the four-factor model to regress, the statistics are based on 10 000 bootstrap resamples and ranked on alpha. Panel A reports the top funds in our sample, while panel B reports the bottom funds of our sample. Columns 3-7 reports the OLS estimate of alpha, the estimated t-statistic of alpha, the parametric p-value, the bootstrapped p-value, and the number of observations for each fund, respectively. The alpha estimates are annualized and reported in percent.

Panel A: Top funds ranked on alpha from Carhart's four-factor model

Fund name	Alpha	t-statistic	Parametric p-value	Bootstrapped p-value	Observations
FIRST Generator	10,95	2,19	0,03	0,55	14
Landkreditt Utbytte	7,62	1,82	0,05	0,10	19
FORTE Norge	6,18	1,43	0,08	0,63	81
DNB Norge R	6,11	1,11	0,15	0,60	12
Landkreditt Norge	5,38	2,15	0,02	0,32	83
Holberg Norge	4,72	0,90	0,19	0,55	37
Storebrand Norge A	4,18	1,24	0,11	0,76	33
Fondsfinans Aktiv II	3,78	1,94	0,03	0,37	205
Danske Invest Norge Aksj. Inst 2	3,26	1,94	0,03	0,21	158
KLP AksjeNorge	3,19	1,15	0,13	0,72	122

Panel B: Bottom funds ranked on alpha from Carhart's four-factor model

Fund name	Alpha	t-statistic	Parametric p-value	Bootstrapped p-value	Observations
SR-Bank Norge A	-7,07	-1,05	0,16	0,00	12
Skandia SMB Norge	-7,08	-1,05	0,16	0,00	12
Globus Norge	-8,34	-1,73	0,04	0,01	95
Globus Aktiv	-8,54	-1,99	0,02	0,01	103
Alfred Berg Vekst	-8,95	-1,72	0,05	0,01	72
FIRST Norge Fokus	-11,89	-1,67	0,05	0,00	32
Skandia Horisont	-12,25	-3,22	0,00	0,16	97
Nordea SMB	-16,93	-3,18	0,00	0,02	70
FORTE Trønder	-18,62	-1,81	0,05	0,01	19
Danske Invest Aktiv Formuesf. A	-19,06	-1,89	0,04	0,01	21

As explained in section 4.7, the t-statistic of alpha is more suited for statistical inference. Since the standard error of the alpha normalizes the t-statistic, the highest alpha-value does not necessarily give the highest t-statistic. The amount of risk taken and the lifetime of the fund are the most significant factors for this. For instance, funds that are highly ranked on alpha and have achieved this by taking a higher risk might not be as highly rated when the funds are sorted on the t-statistic of alpha in Table 6. Considering the statistical advantages of the t-statistic, going forward, the basis of inference when evaluating the funds will be the actual and bootstrapped t-statistic of alpha.

Table 6 – Bootstrapped results ranked on t-statistic of alpha

The table provides the cross-sectional bootstrapped results of all Norwegian mutual funds in our sample from 1987-2019. Using the four-factor model to regress, the results are based on 10 000 bootstrap resamples and ranked on the t-statistic of alpha. Panel A reports the top funds in our sample, while panel B reports the bottom funds of our sample. Columns 3-7 reports the OLS estimate of alpha, the estimated t-statistic of alpha, the parametric p-value, the bootstrapped p-value, and the number of observations for each fund, respectively. The alpha estimates are annualized and reported in percent.

Panel A: Top funds ranked on t-statistic of alpha from Carhart's four-factor model					
Fund name	Alpha	t-statistic	Parametric p-value	Bootstrapped p-value	Observations
Danske Invest Norge Aksj. Inst 1	3,02	2,23	0,01	0,82	237
FIRST Generator	10,95	2,19	0,03	0,55	14
Landkreditt Norge	5,38	2,15	0,02	0,32	83
Fondsfinans Aktiv II	3,78	1,94	0,03	0,37	205
Danske Invest Norge Aksj. Inst 2	3,26	1,94	0,03	0,21	158
PLUSS Aksje (Fondsforval)	1,95	1,83	0,03	0,20	300
Landkreditt Utbytte	7,62	1,82	0,05	0,10	19
FORTE Norge	6,18	1,43	0,08	0,63	81
Storebrand Norge Fossilfri	1,60	1,36	0,09	0,65	237
Storebrand Norge A	4,18	1,24	0,11	0,76	33
Panel B: Bottom funds ranked on t-statistic of alpha from Carhart's four-factor model					
FORTE Trønder	-18,62	-1,81	0,05	0,01	19
Danske Invest Aktiv Formuesf. A	-19,06	-1,89	0,04	0,01	21
Globus Aktiv	-8,54	-1,99	0,02	0,01	103
Alfred Berg Aksjef Norge	-3,32	-2,03	0,02	0,02	115
Alfred Berg Aksjespar	-4,98	-2,14	0,02	0,02	106
GAMBAK Oppkjøp	-4,28	-2,45	0,01	0,00	152
Nordea Norge Verdi	-6,44	-2,63	0,00	0,01	213
GJENSIDIGE AksjeSpar	-5,31	-2,96	0,00	0,01	104
Nordea SMB	-16,93	-3,18	0,00	0,02	70
Skandia Horisont	-12,25	-3,22	0,00	0,16	97

We can see many of the same funds in Table 6, as well as the same trends regarding p-values in panels A and B. We do not observe any significant p-values among the top-performing funds in panel A, whereas the worst-performing funds in panel B still have all but one significant p-value. The lowest p-value among the top-performing funds is still 0.11, generated by the same fund, "Landkreditt Utbytte". The fund is, however, ranked seventh sorted by t-stat compared to second sorted by alpha. This fund likely exhibited higher standard errors for alpha than "FIRST Generator", which only went down one spot. We, therefore, come to the same conclusion here as we did for panel A in the previous table sorted by alpha. We cannot reject the null hypothesis of zero abnormal performance ($H_0^+ : \alpha_i = 0$), and we cannot conclude on the existence of skill among the top performers. It seems the top performers are merely lucky. In panel B, the lowest-performing funds have been replaced by "Nordea SMB" in second place and "Skandia Horisont" in first place, moving up from third and fourth place, respectively. All the significant funds in panel B still have significant bootstrapped p-values well under the 0.05 significance level. However, we do see a slightly higher average bootstrapped p-value among the bottom funds. The results among the worst performers support the alternative hypothesis ($H_A^- : \alpha_i < 0$), so as we did in Table 5, we can reject the null hypothesis of zero abnormal performance ($H_0^- : \alpha_i = 0$). We can conclude that 9 out of 10 of the worst-performing funds in our sample do underperform due to a lack of skill and not due to luck (misfortune). "Skandia Horisont" produced an insignificant p-value but notably had the fourth-lowest alpha.

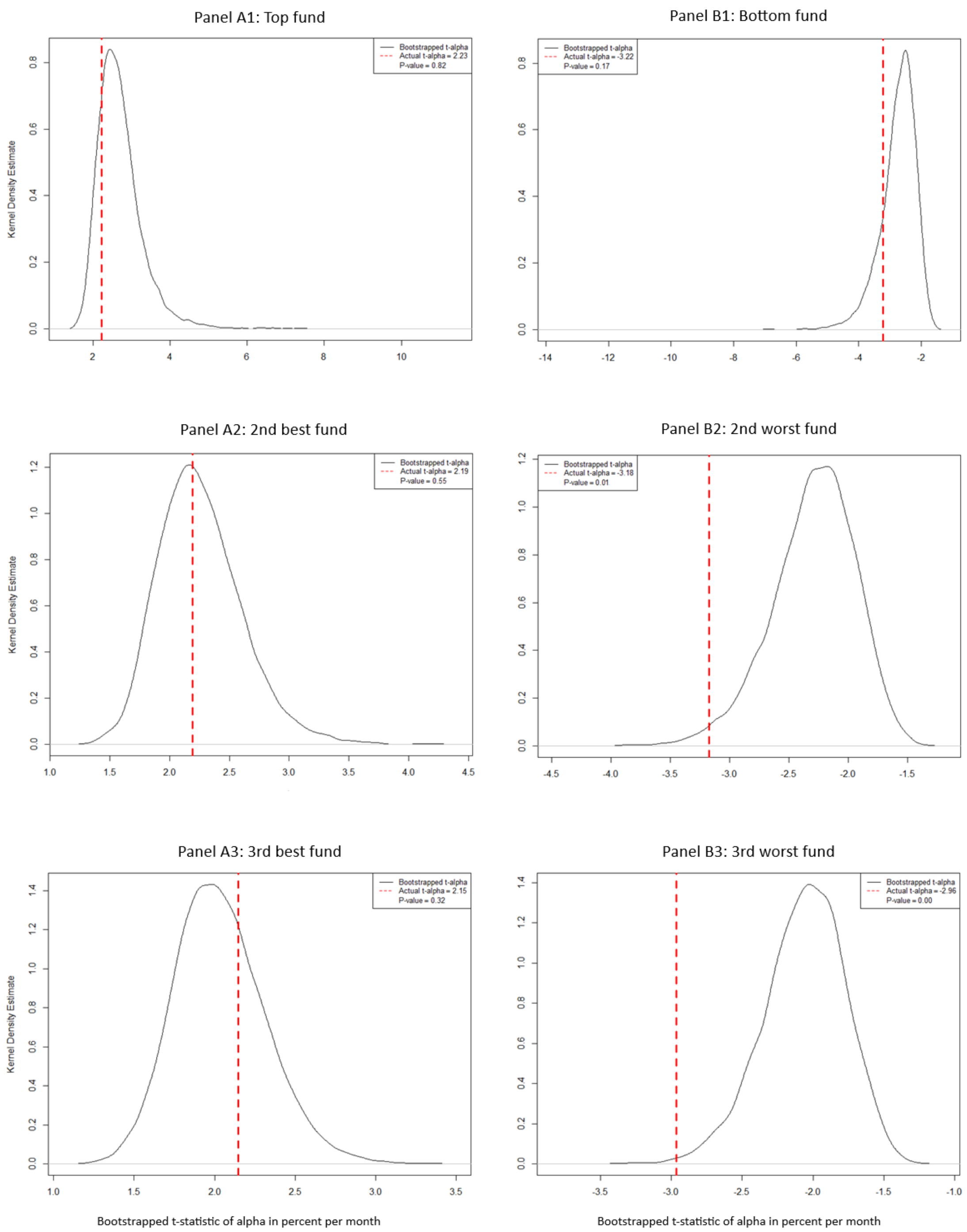
What is interesting is the change of observations among the funds, as this is one of the main factors that affect the calculation of the t-statistic of alpha. Some of the funds with a lower lifespan appear to have been switched out with more established funds as the standard errors of the younger funds have been normalized. However, we still have some funds with a low number of observations present in our table, which likely means that these funds have maintained consistent negative or positive alpha returns during their short lifespan. As we compare the parametric p-values to the bootstrapped p-values, we can see a significant difference, especially among the top performers. As the top performers generated higher bootstrapped p-values compared to their parametric p-values, the bottom performers in most cases did the opposite, thus underlining the importance of the bootstrap procedure in the evaluation process.

To elaborate on the previous inferences made from the bootstrapped results in Table 5 and 6, I use the Kernel density estimate to compare the actual t-statistic of alpha and the bootstrapped t-statistic of alpha, both as individual funds and as mean funds. Figure 6 displays the Kernel density distribution of the bootstrapped t-statistic of alpha for the top and bottom three funds. The dotted red lines illustrate the funds' actual t-statistic of alpha. Panel A1-A3 on the left displays the right tail of the bootstrapped t-statistic distribution along with the top three funds, whereas panel B1-B3 on the right displays the left tail of the bootstrapped t-statistic distribution along with the bottom three funds. The top three funds are left-skewed, but panel A1 is prominent with a higher bootstrapped distribution of alpha t-statistics. It reports an actual alpha t-statistic of 2.23 but generates an insignificant p-value of 0.82, as reported in Table 6. The reason for its insignificance is the bootstrap generating too many t-statistics higher than the actual t-statistic of alpha. This can be seen clearly in panel A1 of Figure 6, as the actual t-statistic of alpha is out on the left side of the distribution. For the top fund to be significant in this case, it would need far more bootstrapped t-statistics on its left side, placing the actual t-statistic further to the right side of the distribution. The connection between the bootstrapped and actual t-statistic of alpha and the significant p-value becomes more visible when looking at panels A2 and A3. Here we can clearly see as the bootstrap generates fewer t-statistics above the actual t-statistic, the p-value decreases. Panel A2 and A3 produce actual t-statistics of alpha of 2.19 and 2.15 along with p-values of 0.55 and 0.32, respectively. These two panels are pretty similar, with both producing bootstrapped t-statistics of alpha in the range of 1 to 4. But as there are no significant p-values among the top funds, the results support the null hypothesis. Therefore, we cannot conclude on the top funds exhibiting skill, but rather that their performances are due to luck.

Panel B1-B3, on the right, display the bottom three funds. The bottom fund produced a t-statistic of alpha of -3.22 and a p-value of 0.17. It was the only fund among the bottom performers that did not produce a significant p-value, and we can therefore not reject the null hypothesis for this fund. The 2nd and 3rd worst funds produced p-values of 0.01 and 0.00 with actual t-statistics of alpha of -3.18 and -2.96, respectively. In Panel B2 and B3, you can see how the bootstrapped t-statistics of alpha are very much on the right side of the actual t-statistic of alpha, indicating that the funds' performances are due to a lack of skill and not mere coincidence.

Figure 6 – Bootstrapped versus actual t-statistic of alpha – single funds

The figures display the Kernel density estimates of the bootstrapped t-statistic of alpha under the null (black line) along with the actual t-statistic of alpha (red dotted line) for the top three and bottom three funds. Top funds are displayed on the left and bottom funds on the right. The Kernel density is shown along the Y-axis, while the t-statistic of alpha is shown on the X-axis. The value of the actual t-statistic of alpha and the bootstrapped p-value is included in the top corner. The statistics are based on 10 000 bootstrap resamples and are ranked on their t-statistic of alpha in all figures.



In addition to looking at the funds individually, I have also estimated the mean of top five and top ten funds using the bootstrapped and actual t-statistic of alpha. The method I use for this is a simplified version of what Fama and French (2010) do in their study, as I only take the mean of the bootstrapped and actual t-statistic of alpha for the top or bottom *n* funds. The results are displayed in Figure 7 using the Kernel density estimate. The figure is divided into four panels. Panels A1 and A2 are the top five and top ten mean funds, respectively, whereas panels B1 and B2 are the bottom five and bottom ten mean funds, respectively. Panel A1 generated an actual alpha t-statistic of 2.09, whereas panel A2 generated an actual alpha t-statistic of 1.81. However, none of the top mean funds managed to produce a significant p-value, both being over 0.50. Panel B1 and B2 generated an actual alpha t-statistic of -2.89 and -2.43, respectively. Both of the panels also produced significant p-values, with the bottom ten mean funds being significant at the 1 % level and the bottom five mean funds being very close to achieving the same with a p-value just over 0.01. The Kernel density estimates of the top and bottom mean funds lead us to the same conclusion as with the individual funds. For the mean of the top funds, we cannot reject the null hypothesis of zero abnormal performance ($H_0^+ : \alpha_i = 0$), indicating that the overperformance among top funds likely results from luck rather than skill. For the mean of the bottom five and the bottom ten funds, we can reject the null hypothesis ($H_0^- : \alpha_i = 0$) at the 5 % and 1 % significance level, respectively. Therefore, we can confidently conclude that the poor performances in panels B1 and B2 result from a lack of skill rather than the fund managers being unlucky. The Kernel density estimate of the mean top and bottom fifteen funds, as well as the mean top and bottom half of all funds, are included in Appendix F and G, respectively. These provided me with the same results as in Figure 7.

Figure 7 – Bootstrapped versus actual t-statistic of alpha – mean funds

The figures display the Kernel density estimates of the t-statistic of alpha for the mean of top five and top ten funds (left) and the mean of bottom five and bottom ten funds (right). The method is a simplified version of what Fama and French (2010) do, as I only calculate the mean of top and bottom funds. The black line represents the mean of the bootstrapped t-statistic of alpha under the null, and the red dotted line represents the mean of the actual t-statistic of alpha. The Kernel density is shown along the Y-axis, while the t-statistic of alpha is shown on the X-axis. The value of the actual t-statistic of alpha and the bootstrapped p-value is included in the top corner. The statistics are based on 10 000 bootstrap resamples and are ranked on their t-statistic of alpha in all figures.

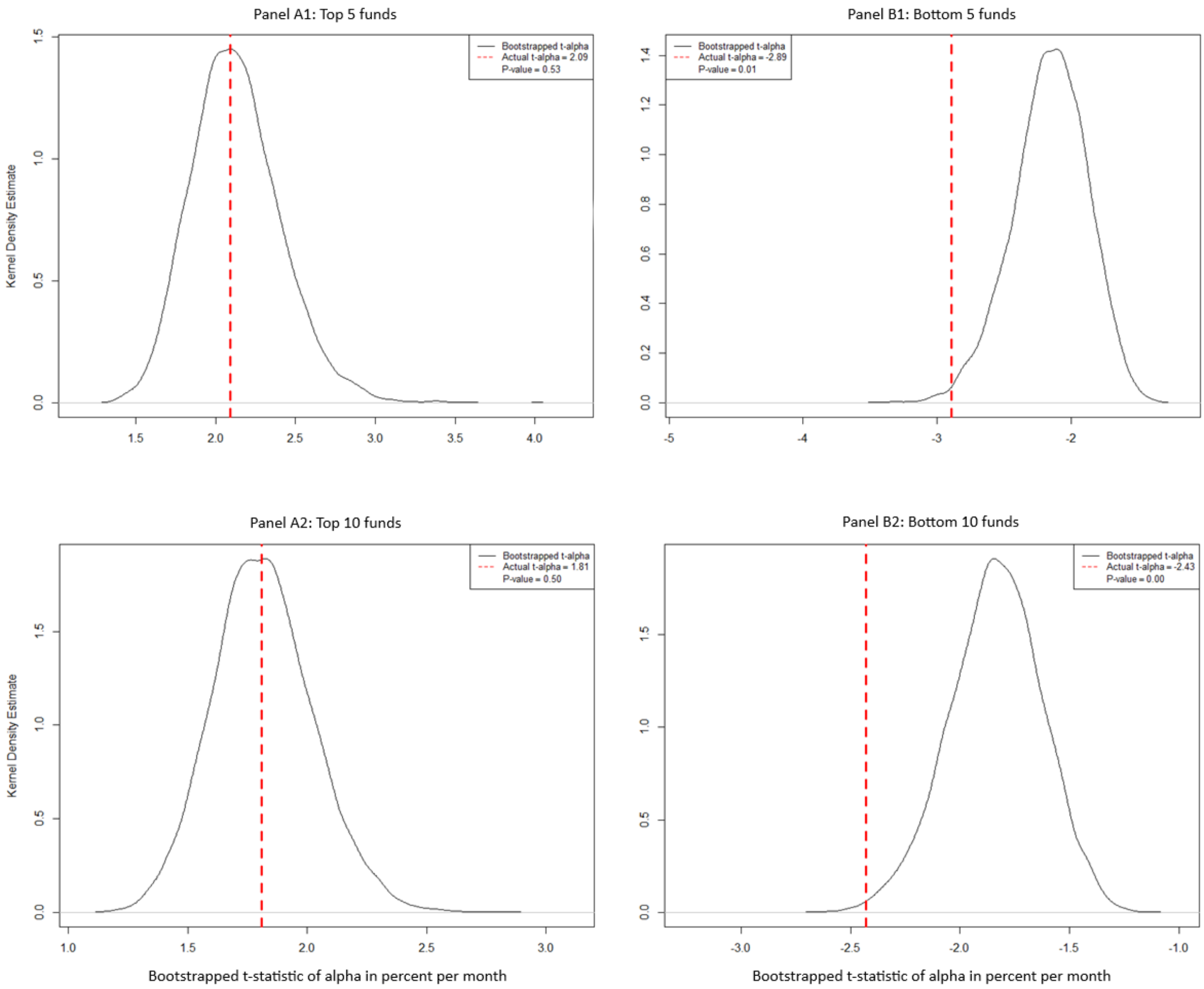
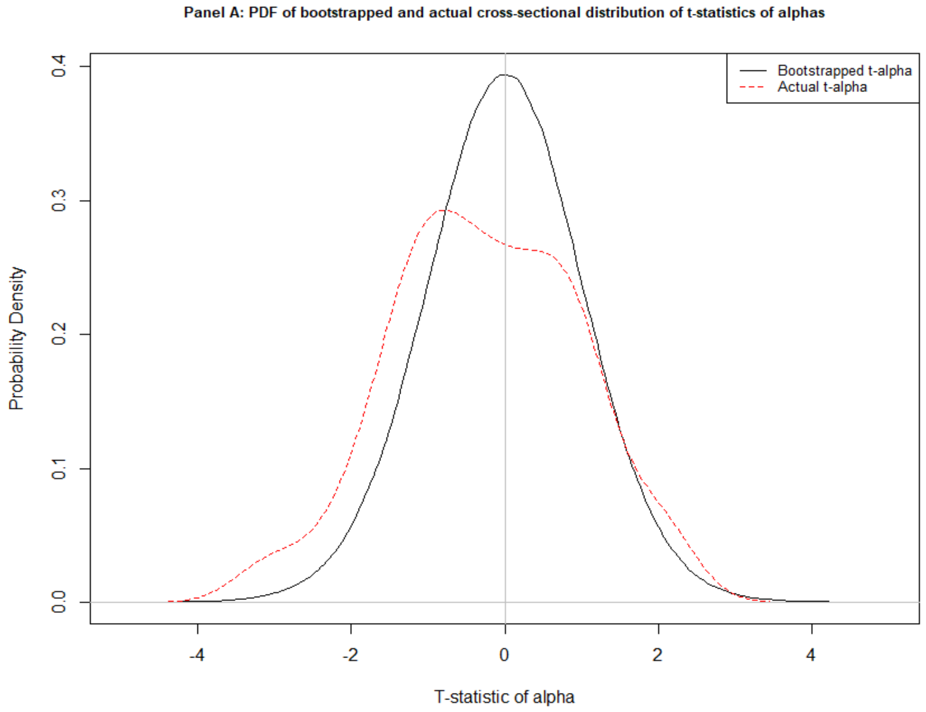


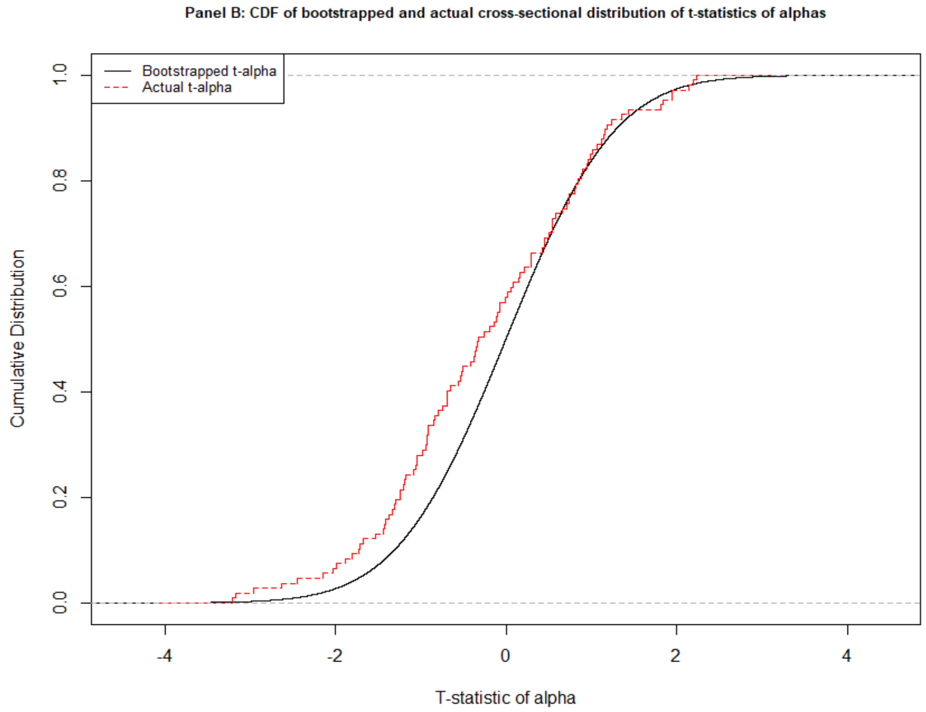
Figure 8 displays the cross-section of the alpha t-statistic. The figure consists of panel A, which plots the probability density function (PDF), and panel B, which plots the cumulative distribution function (CDF). The PDF generally describes the shape of the distribution, and here, we can see that the bootstrapped and actual distribution of the alpha t-statistic differs significantly. The bootstrapped distribution seems fairly normally distributed, whereas the actual distribution of the alpha t-statistic has more mass in its tails, especially the left one. The actual t-statistic of alpha has one distinct top at -1 and shoulders at approximately -2 and 0. As stated in section 6.3, 74.77 % of our fund returns and 57.94 % of sampled residuals are not normally distributed. This is again confirmed when looking at the distribution of the actual t-statistic of alpha. The actual alpha t-statistic has fairly the same probability density as the bootstrapped t-statistic of alpha in the right tail. Above the alpha t-statistic of 1 and around 2, the actual alpha t-statistic has a greater probability density, but it evens out at the most extreme values. The actual alpha t-statistic has a distinctly larger probability density from a t-statistic of -1 and down in the negative left tail.

The CDF in panel B calculates the area under the curve to the left of a chosen t-statistic of alpha and. The distribution can be seen very much as an illustration of a t-statistic percentile table. Starting from the top, we can see the cumulative distributions of the bootstrapped t-statistic of alpha and the actual t-statistic of alpha are relatively similar. The actual t-statistic of alpha is first above the bootstrapped t-statistic of alpha before dropping below it at the t-statistic of ca. 2 to 1.8. After this, the distributions pretty much mirror each other down to about a t-statistic of 0.5. Here, both cumulative distributions are approximately 0.7, which means that approximately 70 % of the distributions are under and to the left of this point. Already at the t-statistic of 0, the cumulative distribution of the actual t-statistic of alpha is significantly above the cumulative distribution of the bootstrapped t-statistic of alpha. Roughly 60 % of the actual alpha t-statistic distribution report a t-statistic lower than zero, indicating underperformance. When considering previous results, the distributions of t-statistic of alpha in figure 8 cement the inference of rejecting the null hypothesis for the lowest-performing funds. There is, however, not enough evidence to conclude on the existence of skill among the top-performing fund managers.

Figure 8 – Cross-section of alpha t-statistic

This figure is divided into two panels. Panel A illustrates the probability density function, while panel B illustrates the cumulative distribution function. In panel A, the solid line represents the bootstrapped cross-sectional distribution of the t-statistic of alpha under the null hypothesis ($\alpha_i = 0$)*. The dotted red line represents the Kernel probability density estimated using the actual t-statistic of alpha. In panel B, the Kernel density estimates are based on a cumulative distribution function of the distributions. The t-statistics of alpha in both panels are estimated using Carhart's four-factor model for the period of 1987-2019.*





7. Conclusion

This thesis examines the performance of Norwegian mutual funds between 1987 and 2019. The dataset, downloaded from the TITLON database, comprises 107 actively managed mutual funds' monthly net returns and is free of survivorship bias. When evaluating the funds, Carhart's (1997) four-factor model is used as the primary performance model on both aggregate and individual levels. The results obtained from Carhart's four-factor model are also combined with a bootstrap procedure similar to Kosowski et al. (2006) to distinguish between luck and skill among individual funds.

Through my analysis, I find that actively managed Norwegian mutual funds on aggregate produce a non-significant alpha of 0.04 %. This suggests that the aggregate fund cannot defend its costs as it fails to produce significant risk-adjusted excess return net of fees. In addition, the historical performance of alpha also indicates that the performance of actively managed mutual funds is near indistinguishable from the benchmark index. The findings in the bootstrapped results support this inference.

When evaluating the funds on an individual level using the bootstrapped t-statistic of alpha, I find no statistically significant evidence for the existence of stock-picking skills among top-performing fund managers. Thus, the null hypothesis, $H_0^+: \alpha_i = 0$, cannot be rejected. When looking at the bottom funds, we can see a clear indication of a lack of skill due to the considerable amount of statistically significant negative t-statistics of alpha. Therefore, we can accept the alternative hypothesis, $H_A^-: \alpha_i < 0$, that the worst-performing fund managers in our sample are not simply unlucky but, in fact, lack stock-picking skills.

Using the bootstrapped results for inference is instrumental for the conclusion of this thesis, as the parametric results vary significantly from the bootstrapped results. The findings of this thesis are in agreement with previous research on mutual funds, for instance, Fama and French (2010). The results, however, contradict the findings of Kosowski et al. (2006) regarding skill among top-performing funds. The results of this thesis also support the EMH presented by Fama (1970), as we cannot exclude the possibility of luck among top performers. When considering my results and the substantial cost differences between active and passive funds, the majority of investors are most likely best off investing in a passive, low-cost index fund.

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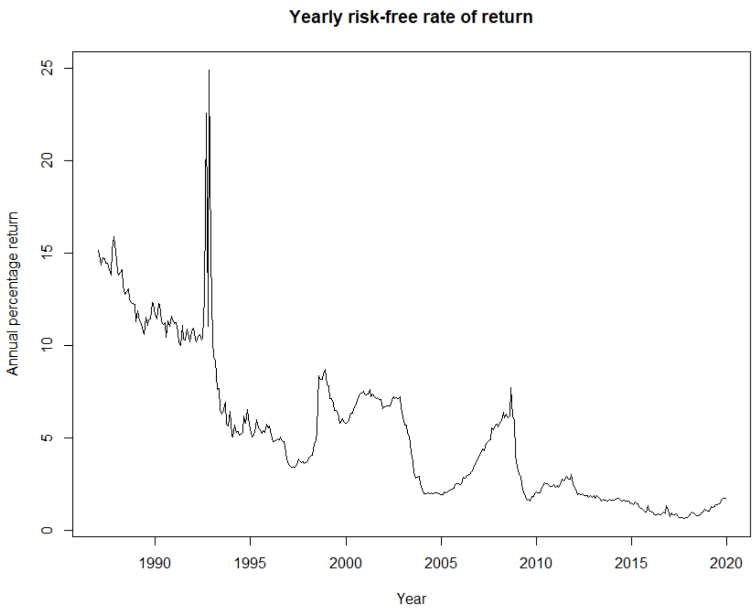
Appendices

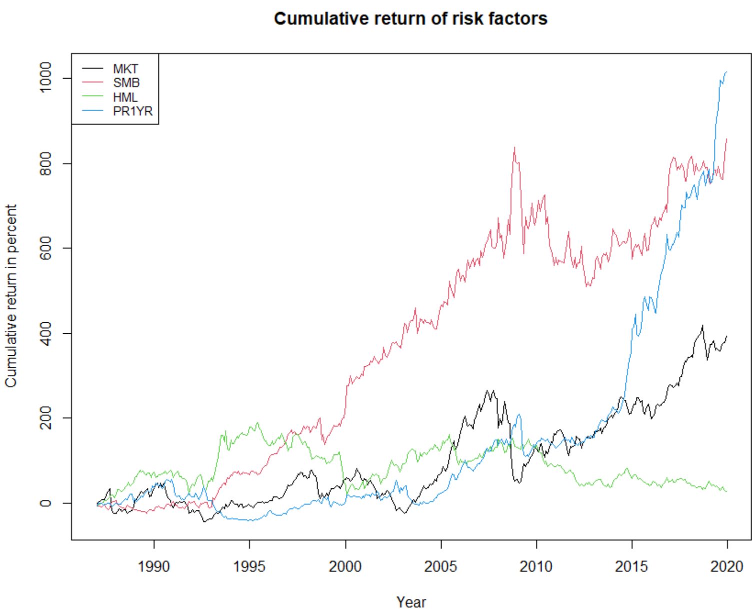
Appendix A – Monthly risk-free rate

The figure displays a plot of the NIBOR one-month risk-free rate of return for the sample period of 1987-2019.



Appendix B – Cumulative return of risk factors.

The figure displays the cumulative return of risk factors in percent for the sample period of 1987-2019.



Appendix C – Individual mutual fund bootstrap results

The table shows individual alpha, t-statistic, parametric p-value, and bootstrapped p-value for each fund in the 107 Norwegian mutual fund sample. Funds are sorted alphabetically, and alphas are annualized and reported in percent. The statistics are based on 10 000 bootstrap resamples.

Fund name	Alpha	t-statistic	Parametric p-value	Bootstrapped p-value	Observations
ABIF Norge ++	0,70	0,29	0,39	0,72	56
Alfred Berg Aksjef Norge	-3,32	-2,03	0,02	0,02	115
Alfred Berg Aksjespar	-4,98	-2,14	0,02	0,02	106
Alfred Berg Aktiv	-1,71	-0,92	0,18	0,00	289
Alfred Berg Aktiv II	-2,93	-1,20	0,12	0,00	182
Alfred Berg Gambak	-0,38	-0,19	0,42	0,02	350
Alfred Berg Humanfond	0,31	0,21	0,42	0,84	241
Alfred Berg N. Pensjon	-3,49	-1,24	0,11	0,00	52
Alfred Berg Norge	1,37	0,85	0,20	0,50	147
Alfred Berg Norge +_gml	-0,01	-0,01	0,50	0,05	197
Alfred Berg Norge Classic	-0,94	-0,93	0,18	0,00	351
Alfred Berg Norge Etisk	-1,23	-0,68	0,25	0,00	146
Alfred Berg Norge Inst	1,30	0,66	0,26	0,50	72
Alfred Berg Vekst	-8,95	-1,72	0,05	0,01	72
Arctic Norwegian Equities Class A	-2,92	-1,30	0,10	0,00	109
Arctic Norwegian Equities Class B	-2,99	-1,42	0,08	0,01	110
Arctic Norwegian Equities Class D	-1,54	-0,69	0,25	0,00	83
Arctic Norwegian Equities Class I	-2,86	-1,37	0,09	0,01	110
Atlas Norge	-1,91	-0,91	0,18	0,00	263
Banco Norge	-2,11	-0,50	0,31	0,00	38
C WorldWide Norge	0,92	0,74	0,23	0,44	294
Carnegie Aksje Norge	1,78	1,15	0,13	0,63	210
Danske Invest Aktiv Formuesf. A	-19,06	-1,89	0,04	0,01	21
Danske Invest Norge Aksj. Inst 1	3,02	2,23	0,01	0,82	237
Danske Invest Norge Aksj. Inst 2	3,26	1,94	0,03	0,21	158
Danske Invest Norge I	0,72	0,55	0,29	0,58	312
Danske Invest Norge II	1,39	1,07	0,14	0,61	312
Danske Invest Norge Vekst	-0,74	-0,33	0,37	0,00	312
Delphi Norge	-0,23	-0,12	0,45	0,04	307
Delphi Vekst	-1,99	-0,74	0,23	0,00	193
DNB Norge	-1,21	-1,44	0,08	0,02	289
DNB Norge (Avanse I)	-1,00	-0,80	0,21	0,00	327
DNB Norge (Avanse II)	-1,72	-1,53	0,06	0,01	287
DNB Norge (I)	-0,19	-0,07	0,47	0,02	295
DNB Norge (III)	-0,06	-0,07	0,47	0,04	283
DNB Norge (IV)	0,17	0,16	0,44	0,89	206
DNB Norge R	6,11	1,11	0,15	0,60	12
DNB Norge Selektiv	0,58	0,50	0,31	0,55	214
DNB Norge Selektiv (II)	-0,38	-0,36	0,36	0,01	307
DNB Norge Selektiv (III)	-2,30	-0,36	0,36	0,01	157
DnB Real-Vekst	1,91	0,71	0,24	0,44	226
DNB SMB	1,71	0,97	0,17	0,56	196
Eika Norge	-1,23	-0,52	0,30	0,00	187
Eika SMB	-3,58	-0,91	0,18	0,00	112
FIRST Generator	10,95	2,19	0,03	0,55	14
FIRST Norge Fokus	-11,89	-1,67	0,05	0,00	32
Fokus Barnespar	-2,49	-0,65	0,26	0,00	48
Fondsfinans Aktiv II	3,78	1,94	0,03	0,37	205
Fondsfinans Norge	-1,04	-0,33	0,37	0,00	107
FORTE Norge	6,18	1,43	0,08	0,63	81
FORTE Trønder	-18,62	-1,81	0,05	0,01	19
GAMBAK Oppkjøp	-4,28	-2,45	0,01	0,00	152
GJENSIDIGE AksjeSpar	-5,31	-2,96	0,00	0,01	104
GJENSIDIGE Invest	-6,13	-1,21	0,12	0,00	88

Appendix C continuation – Individual mutual fund bootstrap results

Fund name	Alpha	t-statistic	Parametric p-value	Bootstrapped p-value	Observations
Globus Aktiv	-8,54	-1,99	0,02	0,01	103
Globus Norge	-8,34	-1,73	0,04	0,01	95
Globus Norge II	0,08	0,06	0,48	0,93	300
Handelsbanken Norge	-3,21	-0,84	0,21	0,00	18
Handelsbanken Norge A10	1,15	0,59	0,28	0,62	229
Holberg Norge	4,72	0,90	0,19	0,55	37
K-IPA Aksjefond	-2,44	-0,97	0,17	0,00	97
KLP Aksjeinvest	0,21	0,15	0,44	0,87	250
KLP AksjeNorge	3,19	1,15	0,13	0,72	122
Landkreditt Norge	5,38	2,15	0,02	0,32	83
Landkreditt Utbytte	7,62	1,82	0,05	0,10	19
Landkreditt Utbytte I	-1,36	-0,85	0,20	0,00	207
NB-Aksjefond	0,48	0,29	0,38	0,78	396
Nordea Avkastning	-3,02	-0,94	0,18	0,00	47
Nordea Barnespar	0,93	0,81	0,21	0,42	298
Nordea Kapital	-0,71	-0,26	0,40	0,01	84
Nordea Kapital II	-3,23	-1,24	0,11	0,00	70
Nordea Kapital III	-0,81	-0,38	0,35	0,01	105
Nordea Norge Pluss	1,35	0,88	0,19	0,50	287
Nordea Norge Verdi	-6,44	-2,63	0,00	0,01	213
Nordea SMB	-16,93	-3,18	0,00	0,02	70
Nordea SMB II	-1,77	-1,31	0,10	0,00	337
Nordea Vekst	1,07	0,55	0,29	0,66	331
ODIN Norge	1,55	0,54	0,30	0,52	50
ODIN Norge A	1,28	0,45	0,33	0,56	50
ODIN Norge B	1,31	0,45	0,33	0,62	50
ODIN Norge D	-0,39	-0,15	0,44	0,03	139
ODIN Norge II	-2,07	-1,06	0,14	0,00	162
Orkla Finans 30	1,80	0,95	0,17	0,49	220
Pareto Aksje Norge	1,25	0,82	0,21	0,48	277
PLUSS Aksje (Fondsforval)	1,95	1,83	0,03	0,20	300
PLUSS Markedsverdi (Fondsforv)	-2,97	-1,17	0,12	0,00	97
Postbanken Aksjevekst	-2,32	-1,09	0,14	0,00	116
RF-Plussfond	-1,01	-0,41	0,34	0,01	47
RF Aksjefond	-7,01	-1,43	0,08	0,01	54
Sbanken Framgang Sammen	-1,68	-0,53	0,30	0,00	67
SEB Norge LU	0,26	0,08	0,47	0,93	97
Skandia Horisont	-12,25	-3,22	0,00	0,16	97
Skandia SMB Norge	-7,08	-1,05	0,16	0,00	12
SR-Bank Norge A	-7,07	-1,05	0,16	0,00	12
SR-Bank Norge B	0,23	0,30	0,38	0,82	282
Storebrand Aksje Innland	-0,20	-0,10	0,46	0,03	226
Storebrand AksjeSpar	0,97	0,74	0,23	0,51	396
Storebrand Norge	-2,27	-0,56	0,29	0,00	43
Storebrand Norge A	4,18	1,24	0,11	0,76	33
Storebrand Norge Fossilfri	1,60	1,36	0,09	0,65	237
Storebrand Norge I	-3,56	-1,33	0,10	0,01	39
Storebrand Norge Institusjon	1,72	1,19	0,12	0,76	221
Storebrand Optima Norge	0,06	0,02	0,49	0,94	328
Storebrand Vekst	1,13	0,99	0,16	0,60	265
Storebrand Verdi	2,32	1,02	0,16	0,63	22
Storebrand Verdi N	-1,28	-0,69	0,24	0,00	187
Terra Norge	1,91	0,42	0,34	0,55	39

Appendix D – Individual mutual fund factor loadings and adjusted R^2

The table reports the factor loadings and adjusted R^2 of each mutual fund in our sample. The statistics have been estimated by running a regression analysis of each fund, using Carhart's four-factor model. The funds are sorted alphabetically. Columns 2-5 report the factor loadings of each fund, while column 6 reports the adjusted R^2.

Fund name	β_{MKT}	β_{SMB}	β_{HML}	β_{PR1YR}	R^2_{adj}
ABIF Norge ++	1,03	0,05	-0,07	-0,05	0,96
Alfred Berg Aksjef Norge	0,98	0,03	-0,07	0,05	0,95
Alfred Berg Aksjespar	1,04	0,02	-0,06	-0,10	0,92
Alfred Berg Aktiv	1,10	0,52	-0,09	-0,15	0,86
Alfred Berg Aktiv II	0,95	0,18	0,00	-0,04	0,87
Alfred Berg Gambak	0,95	0,05	0,03	0,00	0,80
Alfred Berg Humanfond	0,99	0,05	-0,04	-0,01	0,91
Alfred Berg N. Pensjon	1,02	0,05	-0,18	-0,10	0,93
Alfred Berg Norge	1,02	0,00	-0,16	0,00	0,95
Alfred Berg Norge +_gml	0,97	0,04	-0,02	-0,27	0,95
Alfred Berg Norge Classic	1,04	0,55	-0,13	-0,09	0,94
Alfred Berg Norge Etisk	0,53	0,16	0,03	0,01	0,94
Alfred Berg Norge Inst	1,09	0,41	-0,23	0,02	0,84
Alfred Berg Vekst	0,65	0,06	-0,14	-0,10	0,80
Arctic Norwegian Equities Class A	0,96	0,02	-0,06	-0,13	0,75
Arctic Norwegian Equities Class B	1,05	0,21	-0,09	0,03	0,80
Arctic Norwegian Equities Class D	1,00	0,07	-0,02	-0,16	0,76
Arctic Norwegian Equities Class I	1,07	0,03	-0,08	-0,06	0,80
Atlas Norge	1,07	0,12	-0,08	0,03	0,85
Banco Norge	0,97	0,16	0,10	0,00	0,92
C WorldWide Norge	0,99	0,00	-0,05	-0,10	0,92
Carnegie Aksje Norge	0,84	-0,02	-0,08	0,12	0,93
Danske Invest Aktiv Formuesf. A	0,47	-0,10	-0,11	0,03	0,69
Danske Invest Norge Aksj. Inst 1	1,04	-0,07	-0,05	-0,11	0,92
Danske Invest Norge Aksj. Inst 2	1,09	0,31	-0,18	-0,06	0,91
Danske Invest Norge I	1,00	-0,05	-0,03	-0,06	0,90
Danske Invest Norge II	0,84	0,05	-0,10	0,17	0,91
Danske Invest Norge Vekst	1,16	0,28	-0,21	-0,35	0,77
Delphi Norge	0,80	0,03	-0,04	0,05	0,84
Delphi Vekst	0,98	-0,04	-0,05	-0,01	0,84
DNB Norge	1,30	0,27	0,03	0,16	0,96
DNB Norge (Avanse I)	1,02	0,02	-0,08	-0,06	0,92
DNB Norge (Avanse II)	1,30	0,27	0,03	0,16	0,94
DNB Norge (I)	0,96	-0,07	0,00	-0,17	0,74
DNB Norge (III)	1,03	0,07	-0,06	-0,12	0,96
DNB Norge (IV)	1,19	0,47	-0,12	-0,19	0,96
DNB Norge R	1,16	0,31	-0,11	0,16	0,93
DNB Norge Selektiv	0,98	-0,01	-0,06	-0,07	0,95
DNB Norge Selektiv (II)	1,03	0,01	-0,07	-0,01	0,94
DNB Norge Selektiv (III)	1,17	0,25	-0,22	-0,33	0,46
DnB Real-Vekst	1,00	0,01	-0,04	-0,10	0,79
DNB SMB	0,92	0,06	-0,10	0,18	0,89
Eika Norge	0,95	0,01	-0,04	-0,10	0,85
Eika SMB	0,94	0,16	-0,04	-0,12	0,73
FIRST Generator	1,01	0,07	0,00	-0,04	0,77
FIRST Norge Fokus	1,01	-0,04	-0,04	-0,03	0,83
Fokus Barnespar	0,53	0,07	0,03	0,08	0,90
Fondsfinans Aktiv II	1,14	0,27	-0,18	0,03	0,87
Fondsfinans Norge	1,18	0,23	-0,21	-0,32	0,70
FORTE Norge	1,07	0,07	-0,03	-0,01	0,47
FORTE Trønder	1,06	0,03	-0,13	-0,20	0,68
GAMBAK Oppkjøp	1,05	0,25	-0,40	-0,03	0,93
GJENSIDIGE AksjeSpar	0,84	0,02	0,07	-0,07	0,94
GJENSIDIGE Invest	0,97	-0,02	-0,08	-0,08	0,82

Appendix D continuation – Individual mutual fund factor loadings and R^2

Fund name	β_{MKT}	β_{SMB}	β_{HML}	β_{PR1YR}	R^2_{adj}
Globus Aktiv	1,04	0,01	-0,06	-0,09	0,84
Globus Norge	0,98	0,00	-0,04	-0,05	0,81
Globus Norge II	1,46	0,33	-0,07	0,00	0,90
Handelsbanken Norge	1,03	-0,12	-0,07	-0,10	0,90
Handelsbanken Norge A10	1,16	0,30	-0,23	-0,03	0,84
Holberg Norge	1,05	0,13	-0,18	-0,19	0,85
K-IPA Aksjefond	1,00	0,29	0,06	-0,09	0,90
KLP Aksjeinvest	1,03	0,13	-0,04	-0,10	0,92
KLP AksjeNorge	1,05	0,03	-0,16	-0,14	0,83
Landkreditt Norge	1,07	0,11	-0,01	0,02	0,50
Landkreditt Utbytte	0,99	-0,01	-0,09	-0,07	0,60
Landkreditt Utbytte I	1,03	-0,01	-0,08	-0,17	0,92
NB-Aksjefond	1,01	-0,03	-0,06	-0,06	0,83
Nordea Avkastning	1,01	0,03	-0,04	-0,07	0,92
Nordea Barnespar	0,96	-0,04	-0,03	-0,09	0,93
Nordea Kapital	1,00	0,16	0,09	0,02	0,92
Nordea Kapital II	0,95	-0,11	-0,04	-0,07	0,94
Nordea Kapital III	1,04	-0,09	-0,08	0,18	0,84
Nordea Norge Pluss	1,01	-0,02	-0,16	0,03	0,86
Nordea Norge Verdi	0,99	-0,05	0,11	0,01	0,83
Nordea SMB	1,06	0,12	-0,16	-0,10	0,78
Nordea SMB II	1,11	0,20	-0,30	-0,19	0,91
Nordea Vekst	1,11	0,37	-0,29	-0,09	0,79
ODIN Norge	0,94	0,00	-0,05	-0,09	0,77
ODIN Norge A	1,01	-0,03	-0,04	-0,06	0,77
ODIN Norge B	1,00	0,05	-0,02	-0,04	0,77
ODIN Norge D	0,49	0,26	-0,14	0,41	0,82
ODIN Norge II	0,81	0,01	-0,05	-0,02	0,91
Orkla Finans 30	1,13	0,14	-0,27	-0,02	0,84
Pareto Aksje Norge	0,78	0,37	0,39	0,33	0,89
PLUSS Aksje (Fondsforval)	1,10	0,31	-0,27	0,11	0,94
PLUSS Markedsverdi (Fondsforv)	1,05	0,14	-0,05	-0,09	0,92
Postbanken Aksjevekst	0,98	0,30	-0,05	-0,06	0,92
RF-Plussfond	1,00	0,24	-0,10	-0,10	0,84
RF Aksjefond	1,05	0,43	-0,13	-0,12	0,87
Sbanken Framgang Sammen	1,02	-0,02	-0,05	-0,06	0,92
SEB Norge LU	0,99	0,18	-0,04	-0,22	0,86
Skandia Horisont	1,11	0,09	0,21	0,06	0,82
Skandia SMB Norge	0,81	0,01	-0,05	-0,02	0,90
SR-Bank Norge A	0,81	0,01	-0,05	-0,02	0,90
SR-Bank Norge B	0,86	0,33	0,12	-0,14	0,97
Storebrand Aksje Innland	1,06	0,07	-0,09	0,03	0,72
Storebrand AksjeSpar	0,96	-0,04	-0,02	-0,03	0,89
Storebrand Norge	0,95	0,11	-0,01	-0,15	0,92
Storebrand Norge A	1,05	0,05	-0,08	-0,06	0,55
Storebrand Norge Fossilfri	1,06	0,03	-0,08	-0,09	0,94
Storebrand Norge I	0,89	-0,04	-0,04	0,07	0,91
Storebrand Norge Institusjon	1,05	0,02	-0,04	-0,01	0,92
Storebrand Optima Norge	0,73	-0,33	-0,19	-0,03	0,71
Storebrand Vekst	0,82	0,03	-0,08	0,18	0,94
Storebrand Verdi	0,92	0,06	-0,10	0,18	0,93
Storebrand Verdi N	0,96	-0,01	-0,07	-0,07	0,92
Terra Norge	1,01	-0,02	-0,07	-0,05	0,90

Appendix E – Individual mutual fund descriptive statistics

The table reports the descriptive statistics of each mutual fund in the 107 mutual fund sample in the period 1987-2019. The funds are sorted alphabetically after fund names in column 1. Columns 2-8 report, for each fund, the number of observations, the mean return, the standard deviation, the maximum and minimum return, the kurtosis, and the skewness, respectively. The statistics are annualized and in percent.

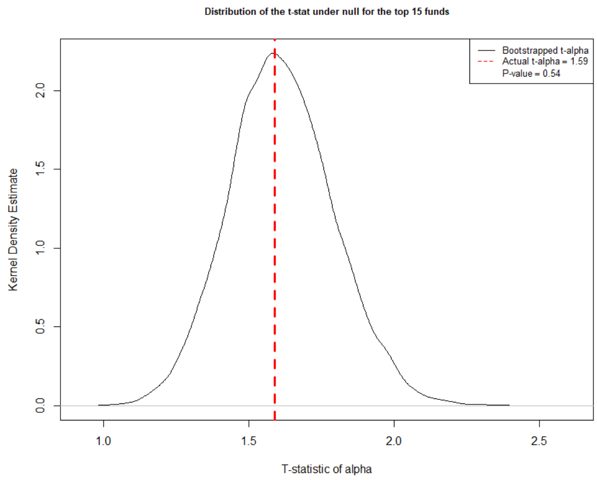
Fund name	Mean	Standard deviation	Maximum	Minimum	Kurtosis	Skewness
ABIF Norge ++	8,02	23,41	13,53	-16,25	-0,47	-0,31
Alfred Berg Aksjef Norge	10,36	21,14	13,06	-24,97	1,88	-0,77
Alfred Berg Aksjespar	9,30	22,90	13,34	-27,99	2,17	-0,87
Alfred Berg Aktiv	14,11	22,62	21,08	-27,05	2,59	-0,77
Alfred Berg Aktiv II	9,27	25,30	17,89	-27,37	1,23	-0,60
Alfred Berg Gambak	15,25	22,68	28,50	-27,38	2,69	-0,40
Alfred Berg Humanfond	10,40	20,27	16,12	-25,88	3,04	-0,97
Alfred Berg N. Pensjon	13,14	21,02	11,91	-24,80	4,56	-1,36
Alfred Berg Norge	10,62	24,59	17,10	-27,01	1,90	-0,96
Alfred Berg Norge +_gml	11,07	23,57	17,13	-26,91	2,23	-0,97
Alfred Berg Norge Classic	10,70	20,99	17,10	-27,01	3,04	-1,06
Alfred Berg Norge Etisk	11,83	23,99	16,65	-27,84	2,58	-1,04
Alfred Berg Norge Inst	12,12	9,64	6,81	-7,98	1,26	-0,95
Alfred Berg Vekst	8,89	26,53	19,33	-27,82	1,89	-0,51
Arctic Norwegian Equities Class A	9,52	11,36	9,49	-9,26	1,51	-0,67
Arctic Norwegian Equities Class B	10,02	12,01	9,79	-9,20	1,44	-0,57
Arctic Norwegian Equities Class D	11,79	9,41	7,11	-8,51	1,55	-0,92
Arctic Norwegian Equities Class I	10,10	11,92	9,65	-9,19	1,41	-0,58
Atlas Norge	10,53	24,20	36,85	-25,25	3,67	-0,09
Banco Norge	13,25	24,05	13,89	-17,12	-0,27	-0,33
C WorldWide Norge	13,40	20,51	19,80	-27,52	3,07	-0,89
Carnegie Aksje Norge	14,47	23,37	19,80	-27,52	2,06	-0,86
Danske Invest Aktiv Formuesf. A	16,69	15,54	7,59	-10,67	0,59	-0,83
Danske Invest Norge Aksj. Inst 1	11,94	19,51	15,46	-22,85	2,69	-0,93
Danske Invest Norge Aksj. Inst 2	10,30	18,72	15,04	-22,73	4,29	-1,16
Danske Invest Norge I	11,17	20,09	14,85	-28,80	3,63	-1,03
Danske Invest Norge II	11,95	20,18	14,91	-29,49	3,64	-1,02
Danske Invest Norge Vekst	15,34	22,27	41,77	-25,68	6,61	0,33
Delphi Norge	15,13	23,39	23,01	-24,93	2,07	-0,54
Delphi Vekst	11,02	26,07	25,54	-23,04	1,03	-0,33
DNB Norge	9,30	20,10	15,81	-24,12	2,38	-0,84
DNB Norge (Avanse I)	10,90	21,89	15,96	-26,42	2,10	-0,96
DNB Norge (Avanse II)	9,65	21,57	16,05	-26,40	2,39	-0,96
DNB Norge (I)	11,48	24,59	59,30	-24,16	15,28	1,31
DNB Norge (III)	10,72	20,25	15,87	-24,17	2,37	-0,87
DNB Norge (IV)	13,95	19,48	15,97	-24,24	2,95	-0,89
DNB Norge R	15,86	9,99	4,48	-5,54	0,70	-1,20
DNB Norge Selektiv	11,99	20,04	16,85	-23,74	2,37	-0,77
DNB Norge Selektiv (II)	11,44	20,05	16,99	-24,07	2,22	-0,82
DNB Norge Selektiv (III)	6,14	30,41	68,90	-40,26	24,68	2,15
DnB Real-Vekst	14,13	23,76	17,48	-26,49	1,17	-0,47
DNB SMB	14,43	19,27	18,40	-24,93	3,96	-1,02
Eika Norge	8,34	23,44	17,06	-22,94	1,28	-0,67
Eika SMB	13,14	19,55	15,51	-18,90	1,41	-0,77
FIRST Generator	11,50	10,02	5,22	-6,09	0,70	-0,99
FIRST Norge Fokus	-0,65	27,06	12,75	-28,09	3,44	-1,21
Fokus Barnespar	-0,60	23,15	14,34	-16,48	-0,07	-0,23
Fondsfinans Aktiv II	16,90	20,17	16,32	-25,73	2,66	-0,78
Fondsfinans Norge	10,00	14,50	14,49	-11,60	1,05	-0,08
FORTE Norge	16,37	11,97	9,46	-8,80	0,27	-0,14
FORTE Trønder	3,50	19,03	13,94	-9,16	0,48	0,35
GAMBAK Oppkjøp	10,54	22,73	16,59	-26,70	2,18	-0,94
GJENSIDIGE AksjeSpar	15,24	20,35	13,34	-21,18	2,39	-0,85
GJENSIDIGE Invest	15,14	29,39	23,56	-22,63	0,35	-0,30

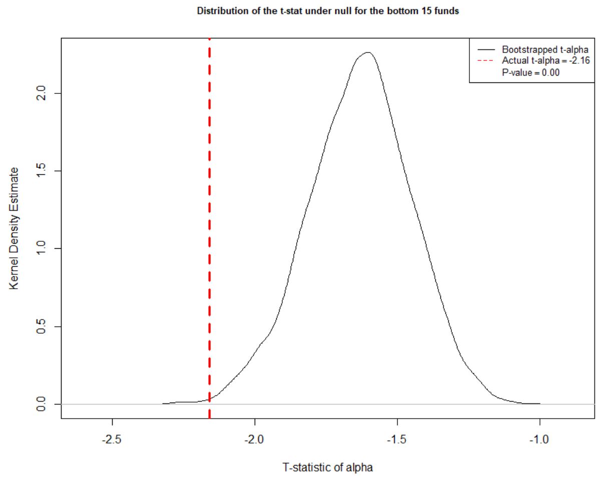
Appendix E continuation – Individual mutual fund descriptive statistics

Fund name	**Mean**	**Standard deviation**	**Maximum**	**Minimum**	**Kurtosis**	**Skewness**
Globus Aktiv	7,71	29,32	22,34	-23,36	0,38	-0,35
Globus Norge	11,98	28,55	23,12	-22,91	0,40	-0,24
Globus Norge II	12,34	20,67	17,75	-28,82	4,08	-1,17
Handelsbanken Norge	3,12	12,61	4,93	-8,50	0,52	-1,18
Handelsbanken Norge A10	11,86	19,79	15,94	-23,90	1,70	-0,52
Holberg Norge	11,49	22,96	12,32	-21,75	2,08	-0,97
K-IPA Aksjefond	5,38	21,14	14,92	-22,21	1,67	-0,78
KLP Aksjeinvest	11,52	20,36	17,59	-29,77	3,24	-0,91
KLP AksjeNorge	7,14	20,38	17,13	-20,70	2,14	-0,74
Landkreditt Norge	13,84	7,31	4,65	-4,68	0,44	-0,76
Landkreditt Utbytte	10,44	7,35	4,21	-3,82	-0,29	-0,39
Landkreditt Utbytte I	9,97	22,50	18,24	-24,78	2,14	-0,94
NB-Aksjefond	11,81	21,95	20,68	-27,57	2,70	-0,87
Nordea Avkastning	-2,20	21,16	11,38	-16,35	-0,32	-0,36
Nordea Barnespar	12,70	20,23	16,70	-25,72	2,92	-1,01
Nordea Kapital	14,40	22,67	13,37	-17,50	-0,20	-0,47
Nordea Kapital II	12,74	23,25	13,33	-17,46	-0,25	-0,56
Nordea Kapital III	10,10	13,32	12,10	-11,09	1,17	-0,65
Nordea Norge Pluss	12,47	18,99	15,17	-24,46	2,66	-0,87
Nordea Norge Verdi	6,80	23,64	18,26	-23,23	0,54	-0,23
Nordea SMB	-13,70	26,47	18,70	-19,14	0,13	0,17
Nordea SMB II	10,62	23,00	19,50	-26,22	1,85	-0,85
Nordea Vekst	15,35	20,88	22,78	-24,09	2,42	-0,43
ODIN Norge	10,85	9,76	4,69	-8,58	1,55	-1,19
ODIN Norge A	10,60	9,78	4,66	-8,63	1,56	-1,20
ODIN Norge B	10,61	9,77	4,67	-8,61	1,56	-1,20
ODIN Norge D	12,24	19,43	13,59	-23,98	3,11	-0,99
ODIN Norge II	18,56	21,83	14,70	-26,16	1,48	-0,71
Orkla Finans 30	13,62	18,55	16,11	-26,09	3,53	-0,84
Pareto Aksje Norge	11,29	20,58	17,56	-25,51	2,32	-0,72
PLUSS Aksje (Fondsforval)	11,75	19,46	15,95	-25,03	3,21	-0,98
PLUSS Markedsverdi (Fondsforv)	7,37	23,68	14,84	-19,72	0,15	-0,40
Postbanken Aksjevekst	10,31	21,45	13,50	-23,83	1,27	-0,73
RF-Plussfond	12,73	9,46	6,72	-7,18	0,81	-0,73
RF Aksjefond	16,89	24,89	14,45	-17,05	-0,53	-0,36
Sbanken Framgang Sammen	-4,99	25,29	15,62	-26,07	1,24	-0,65
SEB Norge LU	11,63	22,30	16,23	-21,52	1,13	-0,76
Skandia Horisont	0,71	23,81	13,83	-27,32	2,44	-1,01
Skandia SMB Norge	16,50	10,17	5,24	-4,64	-0,50	-0,49
SR-Bank Norge A	16,50	10,16	5,24	-4,64	-0,50	-0,49
SR-Bank Norge B	11,33	20,13	15,39	-26,50	3,08	-1,02
Storebrand Aksje Innland	6,75	15,06	10,32	-14,04	1,30	-0,89
Storebrand AksjeSpar	12,76	21,54	17,30	-28,83	2,48	-0,89
Storebrand Norge	23,16	24,49	14,64	-17,17	-0,24	-0,52
Storebrand Norge A	11,18	7,01	4,51	-5,34	1,35	-0,89
Storebrand Norge Fossilfri	11,35	20,56	14,85	-28,59	3,21	-1,00
Storebrand Norge I	8,48	14,62	9,89	-9,72	0,65	-0,53
Storebrand Norge Institusjon	11,84	21,07	14,59	-29,29	3,04	-0,99
Storebrand Optima Norge	15,77	24,02	36,71	-30,06	3,70	0,01
Storebrand Vekst	11,05	20,03	13,50	-26,53	3,18	-0,97
Storebrand Verdi	7,06	10,48	5,92	-5,55	-0,15	-0,53
Storebrand Verdi N	9,47	24,69	18,81	-26,20	1,46	-0,75
Terra Norge	8,57	24,43	11,46	-26,08	3,49	-1,19

Appendix F – Distribution of t-statistic for top and bottom 15 funds

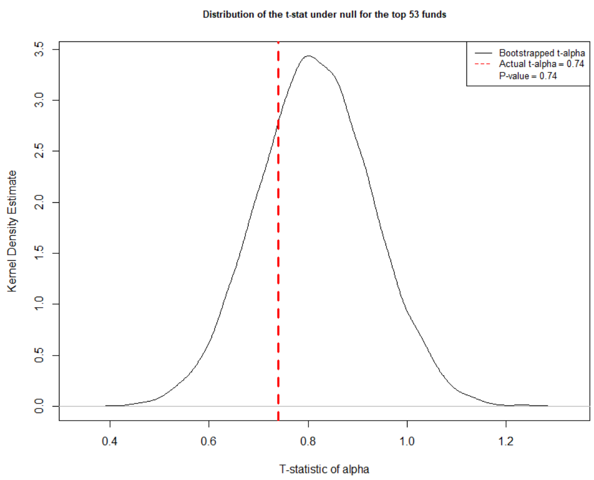
The figures display the Kernel density estimates of the t-statistic of alpha under the null for the mean of top 15 funds (left) and the mean of bottom 15 funds (right). The black line represents the mean of the bootstrapped t-statistic of alpha, and the red dotted line represents the mean of the actual t-statistic of alpha. The Kernel density is shown along the Y-axis, while the t-statistic of alpha is shown on the X-axis. The value of the actual mean t-statistic of alpha and the bootstrapped p-value is included in the top corner. The statistics are based on 10 000 bootstrap resamples and are ranked on their t-statistic of alpha in both figures.

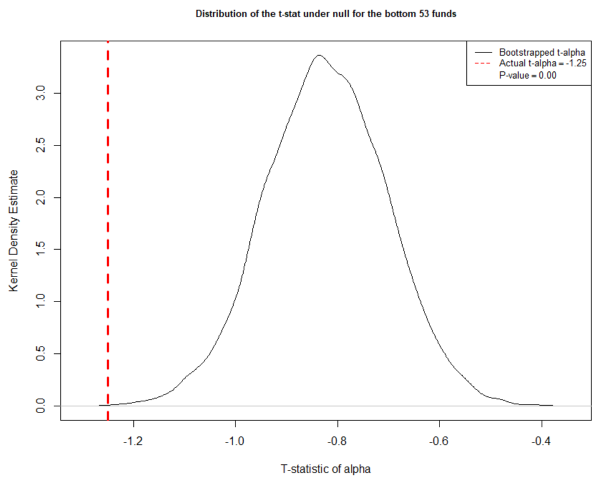




Appendix G – Distribution of t-statistic for top and bottom half of all funds.

The figures display the Kernel density estimates of the t-statistic of alpha under the null for the top half of funds (left) and the bottom half of funds (right). The black line represents the mean of the bootstrapped t-statistic of alpha, and the red dotted line represents the mean of the actual t-statistic of alpha. The Kernel density is shown along the Y-axis, while the t-statistic of alpha is shown on the X-axis. The value of the actual mean t-statistic of alpha and the bootstrapped p-value is included in the top corner. The statistics are based on 10 000 bootstrap resamples and are ranked on their t-statistic of alpha in both figures.





Discussion paper – International

The topic of this paper, "Do Managers of Active Norwegian Funds Possess Stock-Picking Skills?" focuses on the methodology of Kosowski et al. (2006), where the bootstrap method is implemented to evaluate luck versus skill in Norwegian mutual funds. The topic of luck versus skill is widely studied, and it has still not been developed a clear scientific consensus whether active fund managers can justify their cost. The thesis seeks to answer the following research questions

1. Are there Norwegian active mutual funds that manage to produce significant risk-adjusted excess return net of fees?
2. Can we conclude on the best and worst performances not being a result of luck, but rather a result of fund managers' stock-picking skills and lack thereof, respectively?

My thesis evaluates 107 Norwegian mutual funds from 1987 to 2019 and assesses their skill under the null hypothesis of no abnormal performance ($\alpha=0$). All 107 funds are actively managed funds that invest at least 80 % of their total equity in the Norwegian stock market. To allow for a fair benchmark that could explain the funds' performance, the corresponding benchmark used in this thesis is the Oslo Stock Exchange All-Share Index. I replicated the bootstrap methodology of Kosowski et al. (2006) to distinguish lucky and skilled fund managers as well as to distinguish unskilled and unlucky fund managers. The bootstrap procedure is so combined with a regression model that estimates the alpha and t-statistic as well as the p-value of each fund. Using the generated p-values from the bootstrap procedure, we can conclude that the null hypothesis cannot be rejected for the top-performing fund managers as they did not generate significant results below the 5 percent significance level. I.e., we cannot determine whether their overperformance is due to skill or luck. For the bottom ten performers, however, the results are significant, except for the bottom fund. This means that we can reject the null hypothesis and conclude that the bottom funds' underperformance is not only a result of bad luck but a consequence of bad management and a lack of skill. We can see similarities in the results of previous research by, for instance, Fama and French (2010), who also based their work on Kosowski et al. (2006), and also of Blake et al. (2017). Although one can see signs of highly skilled fund managers, the average fund manager does not seem to be able to pick the right stocks. For the investors that want to save their money via a fund, this means that choosing an actively managed fund that will give a positive alpha compared to the benchmark index is close to a fifty-fifty coin toss.

The UIA School of Business and Law has three key concepts in its mission statement and strategy: international, innovative, and responsible. This discussion paper will revolve around the first key concept, "international," and, more precisely, how my thesis relates to international trends and forces. As the thesis takes on the Norwegian trends of a global product, there are many talking points one can get to on this subject. The data I used was strictly taken from the Norwegian market, and by keeping the thesis on a domestic level, I have been able to conveniently compare my study to research done in other countries. The trends and forces I see as most relevant to my thesis today are *actions against climate change (especially ESG)*, *technological trends and advancement*, *increased consumer spending, and governmental regulations and decisions*. Since 2020, the world and the financial markets have been highly affected by the covid 19 pandemic. As my dataset stretched from 1987 to 2019, the recent pandemic is not relevant to my thesis in particular. However, it did affect the financial markets on a large scale during the last two years.

One of the most prominent forces in the last years is the climate-change debate, especially the new ESG-trend (Environmental, Social, Governmental). The public demand for environmentally positive investment opportunities has been high in recent years, and we have seen many companies jumping on the wave of "greenness" to get their piece of the cake. This enormous supply and demand for technological and green investment opportunities have several times been mentioned as a green bubble by, for instance, Finansavisen (Myrseth, 2020) and NRK (Lorch-Falch & Sættem, 2020), amongst others. ESG was something I originally was going to write about, but as the data analysis work grew too big for one student, I put it away and pursued a more manageable thesis on active versus passive investing. However, when going through funds in my research, the focus on ESG was astounding, and I couldn't help but think about the times we've talked about it in different classes as well. ESG is now something that every corporation tries to implement. And as there is a demand for companies to implement ESG, there also comes funds that focus on ESG in their investment decisions. This is essentially a good thing, but there is yet to be a clear international framework for reporting ESG-figures. An ESG-rating can confuse the common investor as the ESG is much more than just environmental factors. In fact, the Norwegian oil company Equinor got the AAA rating from MSCI in 2020 (Equinor, 2020). Therefore, the subject of greenwashing is highly prevalent when we talk about these ratings. How can an investor know for sure what is good and bad for the environment when the ratings themselves are so little transparent? The new ESG reporting frameworks, such as the Sustainable Finance Disclosure Regulation (SFDR), are still being developed further, but hopefully, the ESG reporting system will be more reliable in the future. This is also something that will affect investment vehicles like funds in a large manner as we move forward. Especially active funds will have to endure much more scrutiny when it comes to their investment choices and their supposed claims of positive excess returns.

Technology has been improving at a high rate over the last hundreds of years, and the world is getting more and more connected due to digitalization. The buying and selling funds and stocks for private investors have improved much over the years, with more trading platforms entering the market. Only 20 years ago, you needed to call your broker to put in an order, but now it can all be done by the push of a few buttons on your pc, tablet, or phone. This has also made the world more connected. The funds are all in some way or another connected to the international market since there is no company on the Oslo stock exchange that is not affected by the happenings in other countries. All countries' financial markets were affected by, for instance, the covid pandemic, the Greek financial crisis in 2015, and the financial crisis in 2008. That is because we are all connected now.

The covid-19 pandemic has accelerated the transition for many companies with new ways of working remotely, if it is for meetings or simply working from home when needed. This will likely continue to affect how funds work and how they are delivered to customers, be it if they need smaller staff or if they can better streamline their production. As index funds are so cheap, the funds will likely have to be cut costs where they can, so they actually can give the customers what they are paying for. Technological advancements will likely affect the funds' decisions in the years to come.

Increased consumer spending is another factor that could affect funds significantly in the years to come. In the last ten years, we have seen an increase in assets under management (AUM) from NOK 246 billion in 2011 to NOK 775 billion in 2020. (VFF, 2020). And the percentage of AUM being placed in passive index funds over active funds has risen from 13 % to 26 %. (VFF, 2019). After experiencing a setback like the covid 19 pandemic and just beginning to get back in 2022, I see it likely that people will spend (and save) more money now than they used to before. The increase in AUM will likely not continue at this rate forever, but as funds' AUM increases, the expected responsibility for a fund increase. The more money a fund manages, the more people are affected by its decisions. And according to the results in my thesis, the funds do not seem to be delivering the return they are promising. If we were to look at other actual companies in other industries, they would be more susceptible to harsher critique and more likely to receive some economic punishment, but this has not been the case among funds when they cannot guarantee what they promise. They simply "try to their best capabilities" to beat the market and collect their management fee no matter the outcome.

The government holds great power over the market. They and the central bank control Norway's fiscal and monetary policies, and by, for instance, increasing or decreasing the interest rates, they can effectively slow down or speed up the growth within the country. By changing the interest rate levels, the government can change how much money flows in and out of the country. The level of tax is another way to control spending. The government has the power to keep the economy in check and balance price stability and financial stability. The decisions of the government will affect the Norwegian equity market in the short or long run.

David J. Teece put forward the theory on dynamic capabilities. Teece et al. (1997) explain that dynamic capabilities are an organization's ability to renew, expand and recreate its strategic capabilities to meet the demands of an environment in change. He puts forward three steps to secure dynamic capabilities: discovering opportunities, seizing the opportunity, and reconfiguring. Fund managers of actively managed funds are mainly in charge of producing an excess return for their investors. But they should also be on the lookout for new opportunities. Maybe that is a demand to be made by their customers, who, in the end, are paying them to manage their savings. As most funds cannot reach the goal they have set for themselves, they must look for new ways to compete. However, how this should be done when we are talking about active funds is hard to give sufficient answers to. In my thesis, I concluded that good fund managers are lucky and bad fund managers lack skills. I was, therefore, unable to justify investing in active funds as they cannot back up their claims on a larger scale. There is no way for investors to know what fund to invest in to get a positive alpha return, and therefore, an index fund would likely be a better choice of saving method. In my thesis, I wrote about the Efficient Markets Hypothesis (EMH) and how supporters of passive management often used this as their arguments against active investment. Most funds yield a return not significantly different from the benchmark index, and the ones that produce significant positive or negative are due to luck or bad management. The empirical results of my thesis, as well as the majority of research I have read, point to the EMH being reasonably accurate when it comes to the distribution of fund returns. It seems most funds are operating with a too high fee to justify their costs. The ESG-trend is likely going to get bigger, but there is still reason for concern when it comes to greenwashing. We need a functioning system when looking at ESG-ratings, and hopefully, the new ESG framework will do just that. I am excited to see the future development in actively managed fund returns and if their AUM continues to grow at such high rates.

References – Discussion paper

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