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ACTIVE VS. PASSIVE MUTUAL FUND PERFORMANCE IN THE NORWEGIAN MARKET

Master Thesis

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ABSTRACT

This master thesis examines the performance of active mutual funds in Norway and explores whether actively managed funds consistently outperform passive index funds net of fees. By analyzing a survivorship bias free dataset of 109 active funds spanning the period 1993-2023, we adopt a comprehensive approach to assess the aggregate and individual performance of these funds, while also distinguishing between luck and skill. Our findings reveal that, on aggregate, active fund managers produce a monthly alpha of 30 bps, although being statistically insignificant when employing the Fama-French model. Further, upon examining each individual fund, our findings indicate that a mere 11% of the active funds exhibit outperformance. Our bootstrap analysis provides compelling evidence attributing the observed outperformance to chance rather than skill. Furthermore, our examination of the cross-sectional distribution of alphas reveals the presence of ten fund products exhibiting underperformance in the left tail contributory to skill.

Acknowledgements

We stand at the pinnacle of our MSc in Finance studies at BI Norwegian Business School, having traversed the challenging yet rewarding path of writing this thesis. It is with a sense of accomplishment that we present our final work, the culmination of months of dedicated effort.

First, we thank our supervisor, Janis Berzins, for his feedback and guidance throughout the writing process. We also wish to thank our significant others, family, and friends for their continual support, understanding and encouragement throughout this journey.

Now, we look forward to carrying the knowledge and experiences gained during this program into our future endeavors.

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1 Introduction and motivation

This thesis investigates the performance of actively managed equity mutual funds in Norway, analyzing both the aggregate performance and the performance at the individual fund product level. Additionally, we aim to determine whether the observed overperformance or underperformance of these active funds can be attributed to genuine skill or if it is merely a result of favorable or unfavorable circumstances over time. This essentially boils down to the crucial and intriguing question of whether actively managed funds have the ability to consistently outperform passive index funds after accounting for fees, and whether such performance can be attributed to skill or luck; a question which holds academic and practical significance for multiple reasons.

Firstly, active fund management serves as a widely adopted strategy across diverse categories of investors, encompassing individual retail investors, institutional investors, pension funds, and asset management firms. Understanding its effectiveness is crucial for these investors, as they rely on these funds to achieve superior returns or strive to generate abnormal returns themselves. Secondly, the debate of passive vs. active investing has drawn attention and discussion within the investment community for several decades. Proponents argue that asset managers can consistently outperform the market through their adeptness in stock-picking which allows them to identify undervalued or promising stocks using comprehensive fundamental analysis, selecting companies with strong growth potential or attractive valuations. Additionally, these managers can time market cycles by utilizing technical indicators and market trends to anticipate turning points and exploit market inefficiencies. They adjust portfolios accordingly, seeking to benefit from market upswings while safeguarding against downturns. Moreover, active risk management can play a vital role as managers actively monitor and adapt portfolio allocations, implement diversification strategies, and employ hedging techniques to mitigate risks and capitalize on market opportunities.

Skeptics, however, assert that active management is predominantly influenced by luck rather than skill and they put forward several arguments to support their perspective. They often refer to the Efficient Market Hypothesis (EMH), which posits that financial markets are highly efficient and all available information are already incorporated into stock prices (Fama, 1970). They also argue that the persistence of outperformance is limited, suggesting that even if some managers achieve short-term success, it is difficult for them to sustain it over the long term. Emphasize is therefore put on the role of randomness in short-term investment outcomes, suggesting that some managers may experience periods of outperformance purely by luck rather than true skill. Additionally, skeptics highlight the high costs and fees associated with active management, which can erode returns and make it harder for managers to deliver superior net performance.

Through our empirical investigation, we aim to augment the existing body of scholarly research and contribute valuable insights into the net performance of active funds in the context of the Norwegian market. To achieve this, we utilize a robust dataset of 109 active funds covering a substantial 30-year period from 1993 to 2023. By adopting established financial models like the Capital Asset Pricing Model (CAPM), the Fama-French three-factor model, and the Carhart four-factor model, we are able to assess the ability of active fund managers to generate excess returns beyond the systematic contributions of factors such as market risk, size, value, and momentum, on both an aggregate and individual fund level.

Furthermore, employing a rigorous bootstrapping technique with 10.000 iterations, we evaluate the probability of the observed alphas being attributable to sampling variation (luck) rather than genuine skill, yielding valuable insights into the capabilities of fund managers.

Our findings reveal, after constructing an equally-weighted portfolio and regressing it's excess return on the CAPM, that we obtain a statistically significant monthly alpha of 20 bps. This primary result is indicative of active management outperforming on aggregate. However, when we next augment the CAPM and include the SMB and HML factor in line with Fama and French's (1992) three-factor model, the statistical significance of the alpha vanish. Instead, the SMB factor exhibit statistical significance, indicating that the risk of investing in small-cap stocks explain the variation in returns of the aggregated portfolio along with the risk associated with the fluctuations in the overall market. Further augmentation of the model reveals no statistical significance relating to the momentum factor. The overall aggregate analysis therefore show no evidence of active management outperforming the market net of fees.

However, the individual analysis find evidence that 11% of active managers are able to beat the market after accounting for fees. The best performing funds identified in decreasing order is: (1) SpareBank 1 Norge Verdi, (2) Danske Invest Norske Aksjer, (3) Fondsfinans Utbytte, (4) Storebrand Verdi, and (5) Pareto Aksje Norge. These funds consistently exhibited statistically significant positive alphas, and implemented strategies centered on investing in undervalued large-cap stocks with high book-to-market ratios.

After we built the cross-sectional distribution of alphas from our bootstrap analysis with 10.000 iterations, no evidence of skill were found in the right tail of the distribution. The observed outperformance from these funds are therefore a result of luck, and not attributed to genuine stock-picking or market timing abilities. However, signs of "skill" were found in the left tail. Indicating that some of the active managers who underperformed the market did so not because they were unlucky, but because they actually are bad at picking the right stocks or don't have the ability to time the market, thus destroying value for their investors.

2 Literature Review

The literature review provides an overview of three parts: (2.1) past studies on mutual fund performance, (2.2) evidence from Norway, and finally (2.3) the role of luck and skill in these performances. The primary objective of this section is to lay a solid scholarly foundation for the subsequent findings presented in this thesis.

2.1 Past Studies on Mutual Fund Performance

Harry Markowitz introduced the world to the topic of portfolio theory through his paper "Portfolio Selection" (1952). The idea was that diversification (investing in multiple assets and asset classes) could reduce the risk of holding each individual financial asset. His contribution to the field of financial research landed him the Nobel memorial prize in economic sciences in 1990, along with William Sharpe and Merton Miller. Sharpe (1964) and Lintner (1965) expanded upon Markowitz's work and contributed to the development of the Capital Asset Pricing Model (CAPM), which still remains a cornerstone of economic theory. The model plays a fundamental role in performance measurement and was further developed by Jensen (1968) when he derived a risk-adjusted measure of portfolio performance (today known as Jensen's Alpha) that estimates how much a manager's forecasting ability contributes to the fund's returns.

Sharpe (1966) later introduced the Sharpe ratio as a performance measurement tool for evaluating the risk-adjusted performance of U.S. mutual funds. Unlike the Treynor ratio developed by Treynor (1965), which only takes into account the portfolio's systematic risk, the Sharpe ratio considers the total risk of the portfolio. From his analysis, Sharpe found that only a small percentage of the outperforming funds continued to outperform over time. However, when considering the results as a whole, Sharpe concluded that investing in actively managed mutual funds was generally a poor investment decision, as the mutual fund managers in his sample focused on evaluating risk and diversification rather than spending time on searching for mispriced securities.

Kraus and Litzenberger (1976) examined the CAPM's potential inconsistencies by using a three-moment valuation model, which took into account the effect of systematic skewness. Prior to their study, the CAPM had faced criticism for having an intercept that was deemed too high, as well as a predicted slope that was considered too steep. However, after analyzing the model through their methodology, they found that these initial criticisms were unwarranted.

As previously mentioned, Jensen (1968) developed Jensen's alpha. Based on the CAPM, Jensen's alpha is used to evaluate the risk-adjusted returns for mutual funds. In theory, an actively managed mutual fund should generate a positive alpha, while a passive index fund should produce an alpha of zero. From his analysis however, Jensen concluded that on average, the mutual fund managers were unable to generate a positive alpha.

Grinblatt and Titman (1989) proposed a new model to investigate the presence of abnormal performance in mutual funds. They used the Jensen measure and controlled for survivorship bias to arrive at the conclusion that abnormal returns do indeed exist, particularly among growth funds and small asset value funds. However, the consistency and skill of such returns tended to decline with increasing fees and expenses.

In a later article, Grinblatt and Titman (1992) proposed a somewhat positive persistence in mutual funds' performance, indicating that past performance could be used to some extent in evaluating future performance. This article suggests that the mutual funds that performed well in the past have a better chance of doing well in the future, but also acknowledging that past performance does not guarantee future results.

Ippolito (1989) conducted a study of U.S. mutual funds and found that net of costs, mutual funds outperformed the S&P 500 index. However, the choice of benchmark - with which mutual funds' performance are measured - is important. Lehmann and Modest (1987) found that as Jensen's alpha can be affected by the choice of benchmark, an appropriate benchmark is necessary to accurately represent the common factors driving security returns. Elton, Gruber, and Blake (1996) subsequently examined the findings of Ippolito (1989) and discovered that the funds in Ippolito's sample had a high proportion of small stocks not included in the S&P 500 index, which contributed significantly to their outperformance. They argued that the use of an inappropriate benchmark by Ippolito resulted in the finding of a positive alpha. When adjusting for this factor, the positive alpha became negative.

Wermers (2000) study of mutual funds is another example of a paper receiving critique due to its choice of benchmark. He conducted a study of U.S. mutual funds and found a difference of 2.3% in returns between the average mutual fund and the return on stock holdings. This difference was largely attributed to expenses and transaction costs, with the remainder attributed to the underperformance of non-stock holdings. However, Moskowitz (2002) critiqued the use of benchmark in Wermers' study, arguing that the benchmark applied consisted of small, risky firms that generally performed poorly during the sample period, leading to a skewed result. As a result, Moskowitz suggested that the findings of Wermers may have been inflated due to the choice of benchmark.

The paper by Malkiel (1995) suggests that U.S. mutual funds tend to underperform the market. Analyzing the period from 1971 to 1991, he found that the returns of the mutual funds examined did not show evidence of the ability to beat the market. This underperformance can be explained in part by the fact that the choice of benchmark can impact the results.

To address this issue, multi-factor models were developed to take into account market anomalies. One of the most widely used and well-known of these models was introduced by Fama and French (1992) and is known as the three-factor model. It builds on the single-factor model proposed by Jensen (1968) by adding two additional risk factors to the market factor: size (SMB) and value (HML).

Later, Carhart (1997) added a momentum factor to the three-factor model, creating the Carhart four-factor model. The one-year momentum factor that Carhart included was originally developed by Jegadeesh and Titman (1993) to capture the tendency for prices to continue moving in the same direction for a short period of time.

Fama and French (2015) then developed the five-factor model, which was an extension of the three-factor model as it incorporates two additional risk factors: The profitability factor, which focuses on the relative returns of profitable companies compared to unprofitable ones, and the investment factor, which considers the returns of companies that allocate significant resources to investments compared to those with lower investment levels.

Gruber (1996) investigated mutual funds between 1985 and 1994, looking for reasons as to why investors placed capital in actively managed portfolios, despite of the negative abnormal return when compared to a benchmark. By applying the Carhart four-factor model, his findings suggest that mutual funds underperform compared to a weighted average of indices. Similarly, he investigated the funds gross of fees, and argues that fund managers had abilities to generate abnormal returns, thus possessing stock-picking skills. The skills were not justified however, as it did not cover their fees. He concluded therefore that investing in passive funds was preferred.

2.2 Evidence from Norway

The biggest research conducted in this area in Norway was done by Sørensen (2009). By using a dataset free from survivorship bias to analyze the performance and consistency of all Norwegian equity mutual funds listed on the Oslo Stock Exchange from 1982 to 2008, he found that after controlling for the factors in the three-factor model, there was no statistically significant evidence of abnormal performance in an equal-weighted portfolio of mutual funds. In addition, he used bootstrapping methods to distinguish skill from luck. Only weak signs of skill were found in the top performers, but several underperforming funds were identified in the bottom performers. Overall there was no consistent performance among either the highest or lowest performing funds. Gallefoss (2015) complemented the research by using daily data. By using the bootstrap procedure of Kosowski (2006) they examined the performance of Norwegian mutual funds, and found that on aggregate the mutual funds underperform the benchmark by approximately the fees. However, there are funds with both superior and inferior performance due to skill, and they found strong evidence of performance persistence up to one year.

2.3 Bootstrapping: Skill or Luck

The bootstrap technique to distinguish luck vs. skill for mutual fund managers were first introduced by Kosowski (2006). They examined whether mutual fund managers who had been designated "stars" by Morningstar consistently pick stocks that outperform the market. They used a bootstrap analysis, which we will replicate in our thesis, to assess the likelihood that the outperformance of the "star" funds is due to chance, rather than skill. The results suggest that the performance of these "star" funds is largely due to luck rather than skill, implying that investors should be cautious when relying solely on Morningstar's star ratings when choosing mutual funds.

3 Theory

In this chapter, we highlight the theoretical underpinnings discussed in the literature review and provide a clear distinction between active and passive funds. By doing so, we further solidify the foundation upon which our research is built.

It is important to differentiate between passive and active funds. Passive funds, alternatively referred to as index funds, are investment vehicles designed to replicate the performance of a specific market index (Chen, 2020), such as the Oslo Stock Exchange Benchmark Index (OSEBX). These funds allocate their assets to mimic the weightings and composition of the underlying index. By passively tracking the market, these funds offer investors a diversified portfolio that mirrors the market's overall performance. To illustrate the potential effectiveness of investing in passive funds, we conducted a preliminary analysis using our market benchmark as a demonstration. The findings revealed that even a modest initial investment of 1 NOK in the market index at the start of our study period in 1993 would have yielded a substantial return of 14 NOK to date. Similarly, a substantial investment of 10 million NOK made in 1993 would have grown to an impressive sum of 140 million NOK today. This serves as a compelling illustration of the significant advantages associated with passive investing strategies that align with the overall market's performance.

In contrast to passive funds, active funds are managed by professional portfolio managers who actively make investment decisions based on their market outlook and analysis. These managers utilize strategies such as fundamental analysis, technical analysis, and market timing in their attempts to outperform the market and generate abnormal returns. They claim that their expertise, research capabilities, and market insights can result in superior investment performance compared to index tracking.

However, most scholars believe active management on aggregate does not outperform passive management. This is aligned with William Sharpe's reasoning in his article "The Arithmetic of Active Management" (1991). Sharpe states that the average returns on actively managed investments will be equal to those of passively managed investments before cost, but lower after accounting for the higher fees associated with active funds. Active management should therefore be considered a zero-sum game in gross terms, and a negative-sum game net of fees (Sharpe, 1991). French (2008) supported Sharpe's arguments in his Presidential Address. He presented an average estimate of 67 bps as the aggregate cost that investors incurred in pursuing active returns in US equities over the period 1980-2006 after comparing the fees, expenses and trading costs society pays to invest in the U.S. stock market with an estimate of what would be paid if everyone invested passively. The typical investor would thus increase his average annual return by 0.67% if he switched to a passive market portfolio (French, 2008).

These arguments are built upon The Efficient Market Hypothesis (EMH) that proposes that financial markets are efficient in processing information, implying that it is impossible to consistently achieve higher returns than the market average by using any information that is publicly available. According to the EMH, there exists three forms of market efficiency: (1) Weak efficiency, stating that past stock prices and trading volume cannot be used to predict future stock prices, (2) Semi-strong form efficiency, which build on weak form by stating that all publicly available information, including financial statements and news, cannot be used to consistently beat the market, and finally (3) Strong-form efficiency, which claims that all information, including insider information, cannot be used to achieve higher returns than the market average (Fama, 1970). The most realistic representation of the real-world financial market is the semi-strong form - new information is quickly disseminated and reflected in prices, making it difficult to find and exploit the pricing irregularities. This renders both technical analysis and fundamental analysis useless in generating abnormal returns, unless inside information is used (Malkiel, 2003).

The theory of Modern Portfolio Management (MPT) proposed by Markowitz (1952) also contributes to our understanding, as it suggests that investors aim to maximize return while minimizing risk (assuming that investors are risk averse) in order to achieve a portfolio that is mean-variance efficient, i.e., it can be located on the efficient frontier. Such a portfolio has a certain weight in the different assets that will provide the highest possible return, given a certain level of risk. An essential aspect of the efficient frontier is that no particular point is superior or inferior to another point. Instead, any point situated on the frontier signifies the highest attainable return for a given level of risk aversion. Opting for a portfolio positioned below the efficient frontier implies the potential for attaining a higher return for the same level of risk. Consequently, choosing such a point would be deemed irrational from an investor's standpoint.

Sharpe's proposition again, does not imply that actively managed funds cannot outperform, but rather that other active investors must underperform for them to do so. This nuance leaves the door open for active managers to outperform where they possess some competitive advantage over other active investors (Sharpe, 1991). Malkiel (2003) also acknowledged this; despite being a supporter for the EMH, the presence of investors with varying levels of knowledge and expertise introduces the possibility of irrational behavior and pricing irregularities in the market, thereby making a case for active management. This further reinforces the nuance left open in Sharpe's article (1991) and provides additional support for the idea that active managers can potentially gain a competitive advantage by effectively capitalizing on these pricing irregularities better than their competitors.

4 Methodology

This thesis applies various models to explore the performance of mutual fund managers and whether the outperformance of actively managed funds is due to luck or managerial skill. This section outlines the models we have applied in our research and is structured in a way where we first outline the models used to measure fund performance and then go more in depth on our methodology on how we approach distinguishing luck from skill.

4.1 Measuring fund performance using factor models

To measure a fund's abnormal return, we will use alpha. Alpha compares the performance of a fund to its respective benchmark index and is calculated by subtracting the benchmark's return from the fund's return and is expressed as a percentage. A positive alpha indicates outperformance, while a negative alpha suggests underperformance relative to its benchmark (Chen, 2023). It is a valuable and commonly used tool for investors to evaluate the performance of actively managed funds. To obtain alpha we regress the excess return of an equally-weighted portfolio of all the active funds in the sample, as well as individual regressions, on the factors in the factor models.

"Factor models are financial tools that help investors identify and manage investment characteristics that influence the risks and returns of stocks and portfolios." (MSCI, n.d.). As mentioned in the literature review, Jensen (1968) built on the works of Sharpe and Lintner's CAPM and created a single-factor model to evaluate risk-adjusted returns. Later, Fama and French (1992) developed the Three-Factor Model, consisting of the three factors size, value, and market risk. Carhart (1997) expanded the model by including a momentum factor. In our aggregate analysis, we use all these factor models to evaluate the performance of the asset managers. However, when conducting individual regressions on each fund, we focus solely on the Carhart four-factor model. This specific model effectively captures the variations in returns influenced by all the relevant factors, enabling a more precise evaluation.

4.1.1 Single-Factor Model: CAPM

$$R_{it} - R_{ft} = \alpha + \beta_1(R_{Mt} - R_{ft}) + \epsilon_{it}$$

The single-factor model serves as a simple, yet effective way to compare the performance of active and passive funds. The model calculates the fund's alpha by comparing the fund's return in relation to the benchmarks' - active and passive funds tends to use the same benchmark and can represent the broad stock market or a specific industry/sector. A positive alpha indicates outperformance while a negative alpha suggests underperformance. The risk that is captured by this model is the market risk, i.e., the risk associated with fluctuations in the overall stock market. It is also worth mentioning that the single-factor model has been widely debated throughout the 1980s and 1990s, and has been subjected to significant critique for not being comprehensive enough to explain the return of assets, thus the need for more comprehensive models.

4.1.2 Three-Factor Model

$$R_{it} - R_{ft} = \alpha + \beta_1(R_{Mt} - R_{ft}) + \beta_2 SMB_t + \beta_3 HML_t + \epsilon_{it}$$

Fama and French (1993) sought to enhance the single-factor model by introducing two additional risk factors that contribute to explaining returns. Their proposed three-factor model incorporates a size factor (SMB_t) and a value factor (HML_t) alongside the market risk factor. While market risk factor reflects fluctuations in the overall stock market, the size factor represents the risk associated with investing in small-cap stocks, and the value factor captures the risk of investing in stocks that are trading at a discount to their intrinsic value. This model has become a cornerstone of modern portfolio theory and is the most commonly used model to measure the performance of mutual funds.

4.1.3 Carhart-four factor model

$$R_{it} - R_{ft} = \alpha + \beta_1(R_{Mt} - R_{ft}) + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 PR1YR_t + \epsilon_{it}$$

The Carhart Four-Factor Model was developed by Carhart (1997) and it is an extension of the three-factor model developed by Fama and French (1992). The model adds a momentum factor, ($PR1YR_t$) and are constructed as the equal-weight average of firms with the highest 30% eleven-month returns lagged one month minus the equal-weight average of firms with the lowest 30% eleven-month returns lagged one month and are re-formed monthly (Carhart, 1997). In other words, the momentum factor captures the tendency of stocks to continue their recent price trends.

However, as we do not have Carhart's PR1YR factor available, we use Fama and French's momentum factor, Up-Minus-Down (UMD) instead, as replicated by Ødegaard (2023) on Norwegian data. UMD is the intersection of six value weighted portfolios formed on size and momentum each month. First, Fama and French divide the data into two separate portfolios based on size (market equity, ME), the stocks are then defined as "small" or "big" based on whether they are below or above the median market equity respectively. Second, based on the stock's prior 12 month return, with a two months lag (2-12), it is defined as "up", "medium" or "down" based on the breakpoints 30th and 70th percentile (same as in PR1YR). The UMD factor is then calculated as the average return on the two high prior returns portfolios minus the average return on the two low return portfolios (French, 2023):

$$UMD = \frac{1}{2}(SmallHigh + BigHigh) - \frac{1}{2}(SmallLow + BigLow)$$

There are two main differences between the two momentum factors proposed by Carhart and Fama and French: (1) Carhart's approach uses 11 months prior returns with one month lag, while Fama and French uses prior 12 month returns lagged two months, and (2) Carhart's approach does not consider market equity. Thus, our regression model would instead look like this:

$$R_{it} - R_{ft} = \alpha + \beta_1(R_{Mt} - R_{ft}) + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 UMD_t + \epsilon_{it}$$

As the financial data coverage in Norway has been insufficient until recent years, we have been unable to incorporate the investment factor (CMA) of the Fama and French five-factor model into our analysis. Consequently, we decided to base our analysis on the Carhart four-factor model as it is compatible with the data we have available.

4.2 Bootstrapping: Distinguishing Luck from Skill

As mentioned in the literate review, the bootstrap method to distinguish luck vs. skill among mutual fund managers was first introduced by Kosowski (2006) to examine the performance of the U.S. equity mutual fund industry during the 1962-1994 period. The purpose of their methodology was to uncover whether the mutual funds with the best performance are simply lucky or if their managers possess genuine stockpicking and market timing abilities. Due to the complicated form of the distribution of alphas across funds and the non-normal nature of individual fund‘s alphas, this bootstrap technique was necessary. By bootstrapping the distribution of alphas across mutual funds, they were able to control for luck and determine that fund managers in the U.S. who pick stocks well enough to more than cover their costs do exist. We implement their methodology in a similar fashion, the only difference being that we relax the number of observation constraint, to answer our research question which is limited to the Norwegian market and see if Norwegian fund managers possess genuine stockpicking skills and market timing abilities.

To initiate the bootstrap procedure, we commence by applying the Carhart four-factor model to estimate the alphas, corresponding t-statistics, factor loadings, and residuals. This estimation is performed using the monthly excess returns of a specific fund, identified as fund i.

For each fund i, we draw a random sample with replacement from the fund‘s residuals, $\{\hat{\epsilon}^b_{i,t_\epsilon}, t_\epsilon = s^b_{Ti0}, \ldots, s^b_{Ti1}\}$. The variable "b" serves as an index representing the bootstrap draw, and each of the time indices $s^b_{Ti0}, \ldots, s^b_{Ti1}$ are randomly selected from the interval $[T_{i0}, \ldots, T_{i1}]$ in a manner that reorganizes the orginal sample of resiudals for fund i, while preserving the same length. Further, we construct a pseudo monthly excess return series for fund i, while imposing the null hypothesis of zero abnormal performance ($\alpha_i = 0$):

$$R^b_{i,t} = \hat{\beta}_i(R_{Mt} - R_{ft}) + \hat{s}_i SMB_t + \hat{h}_i HML_t + \hat{u}_i UMD_t + \hat{\epsilon}^b_{i,t_\epsilon},$$

for $t = T_{i0}, \ldots, T_{i1}$ and $t_\epsilon = s^b_{Ti0}, \ldots, s^b_{Ti1}$. By construction, this time-series of pseudo returns has a true value of alpha equal to zero. So, when we next regress the returns for each bootstrap sample, b, on the Carhart four-factor model, we find either a positive or negative estimated alpha due to the random draw of residuals, which may be either abnormally high or low. The aforementioned steps are iteratively applied to all funds, $i = 1, \ldots, N$, in order to obtain a single draw from the cross-section of bootstrapped alphas. By repeating this process again over all bootstrap iterations, $b = 1, \ldots, 10.000$, we construct the distribution of these cross-sectional draws of alphas, $\{\hat{\alpha}^b_i, i = 1, \ldots, N\}$, which results solely from the sampling variability, while having imposed the null hypothesis of zero abnormal performance ($\alpha = 0$). Finally, if we observe a significant disparity between the occurrence of extreme positive values of α in our bootstrap iterations compared to the actual data, it leads us to infer that sampling variation (or luck) alone cannot account for the presence of high alphas. Instead, we can conclude that genuine stock-picking abilities indeed exist (Kosowski, 2006).

In contrast to Kosowski, who perform the bootstrap methodology while imposing a constraint of funds needing at least 60 months of return data to be included, we relax this constraint and allow all funds with at least 12 months of observations to be included in our bootstrap. This is done to account for the fact that our Norwegian sample is much smaller than what you will find in the U.S. and to ensure that our analysis is conducted free of survivorship bias.

5 Data

This section provides an overview of our data collection sources and introduces the Norwegian fund market. Subsequently, we elaborate on the composition of our Norwegian mutual fund sample, while highlighting the importance of a survivorship bias free dataset. Then, we discuss the process of interest rate and benchmark selection, along with the four risk factors utilized in our analysis.

5.1 Introduction to the Norwegian Fund Market

In our analysis we will look at Norwegian mutual, open-ended equity funds. This implies that shares within the funds can be bought or sold at any time, as the fund can issue or redeem shares based on investor demand. This in turn means that asset managers continuously offer new shares at a price reflecting the Net Asset Value (NAV) of the fund. Gjerde and Sættem (1991) found that before 1982 there was only one mutual fund listed on the Oslo Stock Exchange.

In 1982, there was introduced a tax rebate on mutual fund investment, which led to an expansion in the number of funds, so much in fact that in the next 8 years the market value grew from NOK 290 million in 1982 to NOK 8.5 billion in 1990. However, this tax deduction only lasted 10 years (until 1992).

As of 2023, the tax on capital gains from investments in Norwegian mutual funds, provided the fund holds more than 80% equity, is set at 37.84% (Storebrand, 2023). In addition, individuals have to pay wealth tax corresponding to the market value of the investment in the fund as of year-end in the year the tax applies. To avoid double taxation, dividends are not taxed and the funds themselves are exempt from tax.

5.2 Norwegian Mutual Fund Sample

Our fund sample consists of 109 funds, covering the period from 1993 to 2023, which amounts to 360 months. To address survivorship bias, we have intentionally included both "dead" funds (those no longer in operation) and "alive" funds in our analysis. Among the 109 funds, 30 of them are classified as "dead". For inclusion in our analysis, all funds must have a minimum of 12 months of coherent data reported, nine funds were therefore excluded from the original sample. Moreover, we exclusively consider actively managed funds, thereby excluding 10 more funds from the original sample which had "passive", "passiv", "index", or "indeks" in the fund‘s name.

5.2.1 Biases

Survivorship bias occurs when only the successful or surviving funds are considered in the analysis, while excluding those that have ceased to exist or underperformed (Sørensen, 2009). If we were to include only the "alive" funds, the results could be positively skewed, making the overall performance of the funds appear better than it actually was. By including the "dead" funds, we ensure a more accurate representation of the entire fund population and avoid overstating the average performance of the funds.

Also, as one of our inclusion criteria is that a fund needs a minimum of 12 months reported returns, a look-ahead bias may occur. A fund could be short-lived as a result of management fees not covering its expenses, insufficient inflow of cash, merging with another fund or simply underperformance. Either way, excluding funds may affect the overall return of our sample, creating a bias when omitted. (Elton et al., 1996) However, the nine funds excluded were all established within the last year. This means that none of the funds were terminated due to underperformance, resulting in no look-ahead bias beeing created.

5.2.2 Fund return calculation

We use monthly total return from Morningstar Direct as our performance data. The calculation is determined each month by taking the change in monthly net asset value (NAV), reinvesting all income and capital-gains distributions that month, and dividing by the starting NAV. Reinvestments are made using the actual reinvestment NAV, and daily payoffs are reinvested monthly. Morningstar does not adjust total returns for sales charges, but do account for management, administrative, 12b-1 fees and other costs taken out of funds' assets (Morningstar, 2023). The calculation for the monthly returns is as follows:

$$r_t = \frac{NAV_t - NAV_{t-1}}{NAV_t - 1}$$

5.3 The risk-free rate

Accurately computing the excess returns used in our regression analysis necessitates the utilization of an appropriate risk-free rate. In our study, we sourced the risk-free rate data from Bernt Arne Odegaard‘s online resources. Odegaard‘s methodology combines government securities and the Norwegian Interbank Offered Rate (NIBOR) to estimate the forward-looking 1-month risk-free rate. This approach captures market conditions and expectations by reflecting the interest rate for borrowing in the subsequent period (Odegaard, 2023). By relying on Odegaard‘s reputable resources, we ensure the reliability and validity of our analyses by incorporating a well-established source for risk-free rate data.

5.4 Benchmark construction

The most recurring criticism in previous research concerning the topic of our analysis has in large revolved around benchmark selection/justification – one of the most crucial components when assessing a fund's performance. The majority of Norwegian mutual funds use Oslo Stock Exchange Mutual Fund Index (OSEFX) as benchmark. OSEFX mirrors the movements of OSEBX, while complying with UCITS standards. These European Union standards states that "no single asset can represent more than 10% of the fund's assets; holding of more than 5% cannot in aggregate exceed 40% of the fund's assets. This is known as the "5/10/40" rule" (Maples, n.d). The OSEFX is by design capturing these legislations, making it the ideal benchmark for our analysis.

However, our sample predates the initiation of OSEFX by three years as the earliest return data available is from January 1996. As OSEFX is the best fitting benchmark, we must ask ourselves what benchmark would be appropriate to use prior to OSEFX – and we could argue the case for either the MSCI total return index for Norway or the OSE All Shares index (OSEAX) as these are the only two benchmarks with return data dating that far back. The MSCI index includes selected large-capitalization stocks, whereas OSEAX is a combination of all shares listed on Oslo Stock Exchange. We believe that the most prominent benchmark is OSEAX, but the reproduction would require trading in stocks with low liquidity, which could incur significant transaction costs. To conclude the search for a fitting benchmark we first use OSEAX from 1993 to the end of 1995, and OSEFX for the remainder of our analysis, from 1996 to 2023. This choice of benchmark also align with Sørensen's paper (2009).

5.5 Risk Factors

In order to measure Norwegian fund managers' performance, we need risk factors. As previously mentioned, we would have preferred to use the Fama-French (2015) five factor model, but as we do not have this factor available for the Norwegian market, we utilize the Carhart (1997) four-factor model instead.

Using Bernt Arne Odegaard's (2023) online resources we gather 30 years' worth of factor data (HML, SMB and UMD), which is computed as calculated by Fama and French (1998), only using Norwegian data. Lastly, instead of using Carhart's Momentum factor (PR1YR) we use Fama and French's momentum factor UMD, as PR1YR were removed from Odegaards online resources to check the code's reliability (construction methods and differences between the two momentum factors are described in detail in section 4.1.3).

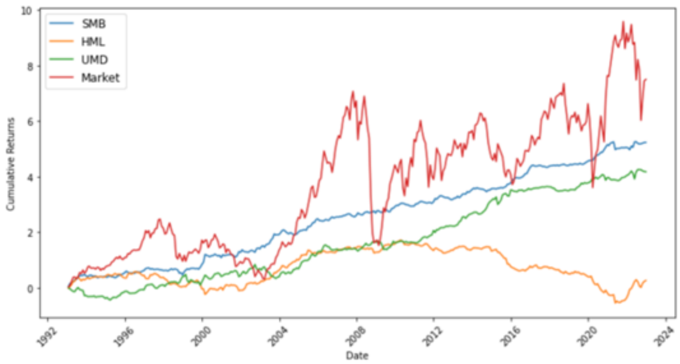

Figure 1: Cumulative returns plot of the CAPM, Fama-French and Carhart factors from the period 1993-2023

6 Results and analysis

In this section we present our analysis of Norwegian mutual fund performance and its results. First, we investigate the performance of both the aggregated dataset and individual performance through factor models. We use three different factor models: (1) the Capital Asset Pricing Model (CAPM), (2) the Fama-French three-factor model, and (3) the Carhart four-factor model. The primary focus however should be on the four-factor model, as this is applied in all later bootstrapping procedures, while the latter models are used for comparison in our analysis. Lastly, we examine the bootstrap results within the framework of Kosowski (2006) to determine whether there is evidence of skilled or unskilled managers within our sample.

6.1 Active fund performance

6.1.1 Aggregate performance

To address the research question pertaining to the potential for Norwegian actively managed funds to consistently outperform their passively managed counterparts, our analysis initiates by examining the overall performance of all active mutual funds included in the sample. This crucial starting point allows for a comprehensive evaluation of the collective performance exhibited by active mutual funds in order to ascertain any evidence of consistent outperformance. By constructing an equally weighted portfolio and regressing the excess return on this portfolio on the CAPM, the Fama-French three-factor model, and Carhart four-factor model, we aim to explore and assess the influence of various factors on the performance of active mutual funds, and additionally by examining the alpha, we can further evaluate whether actively managed funds demonstrate a sustained ability to surpass market performance.

The process of constructing an equally weighted portfolio involves simply assigning equal weights to each constituent fund, to ensure a balanced influence on the portfolio performance. However, an issue arises when dealing with funds that have varying start and end dates as in our dataset. Given that the inclusion and exclusion periods of funds differ in our data, merely assigning equal weights without accounting for the temporal variations may lead to a distorted representation of the portfolio‘s performance. Consequently, it becomes crucial to address this issue by employing a methodology that incorporates time-varying weights, thereby ensuring a more accurate reflection of the performance dynamics across the sample period. The weights we use to construct the equally weighted portfolio is therefore adjusted over time based on the changing availability of funds in each month.

Interestingly, when conducting the first regression analysis, the excess return of the equally weighted portfolio exhibits a monthly positive and statistically significant alpha of 20 bps when regressed on the excess return of the market using the CAPM. This initial observation suggests that active funds on aggregate potentially outperform the overall market. Furthermore, the regression model exhibits a high coefficient of determination ($R^2 = 0.96$), indicating that a substantial proportion of the portfolio‘s excess return can be explained by the market factor. This implies a strong relationship between the portfolio‘s performance and the market‘s behaviour. However, it is essential to consider other factors that may contribute to variations in returns beyond solely market performance.

To address this concern, we augment the model by incorporating the Fama-French three-factor model, which includes the additional factors size (SMB) and value (HML). Upon re-running the regression with these additional factors, a noteworthy shift occurs. The alpha is now 30 bps, but the statistical significance of the alpha diminishes, albeit being positive, indicating that the observed excess returns can be partially explained by factors beyond the market. Specifically, the regression table highlights the statistical significance of the SMB factor. The inclusion of SMB appears to account for the disappearance of the alpha previously identified in the CAPM, underscoring the influence of this factor in explaining the excess returns of active funds on aggregate.

Furthermore, in line with the Carhart model, we introduce a momentum factor, UMD, to our analysis. The results reveal a further decline in the alpha, which remains statistically insignificant. Similarly, the UMD factor itself does not exhibit statistical significance.

Table 1: Equally-weighted portfolio regression results

The table presents the alphas, factor loadings, and adjusted R^2, obtained from the regression results for an equally-weighted portfolio of all the active funds in Norway compared to CAPM, The Fama-French three-factor model and the Carhart four-factor model. The point estimates in the table are accompanied by t-statistics, which are displayed in parentheses below the respective values. To address any potential issues of autocorrelation and heteroskedasticity, the standard errors employed in the computation of t-statistics have been adjusted using the Newey and West (1987) procedure. The sample period is 1993 to 2023.

Aggregate performance						
Model	α	β_m	β_{smb}	β_{hml}	β_{umd}	$R^2 adj.$
CAPM	0.002	0.96				0.96
	(2.4)	(61)				
Fama-French	0.003	0.96	0.1	-0.005		0.97
	(0.4)	(68)	(6.15)	(-0.26)		
Carhart	0.0005	0.95	0.099	-0.006	-0.013	0.97
	(0.63)	(67)	(6.31)	(-0.33)	(-0.85)	

In light of these findings, it is evident that while the initial regression analysis using the CAPM indicated the potential for active funds to outperform the market, the inclusion of additional factors reduced the statistical significance of the alpha. This suggest that the observed excess returns of the portfolio can be partially attributed to factors beyond the market, particularly the SMB factor. Furthermore, the introduction of the UMD factor did not provide additional explanatory power.

Moreover, despite the diminished statistical significance of the alpha when incorporating additional factor when looking at the active mutual fund industry as a whole, it is essential to further investigate whether there are individual active funds that consistently generate returns surpassing the market. To address this aspect, we will proceed with individual regression analyses on each fund, enabling a more thorough examination of their performance characteristics and potential ability to generate alpha.

6.1.2 Individual performance

While the UMD factor was found to be statistically insignificant in the regression of the equally-weighted portfolio, it is possible that individual funds may exhibit different sensitivities to this factor. We therefore perform the individual regressions using the Carhart four-factor model to capture any potential influence it may have on the performance of individual funds.

To perform the individual regressions using the Carhart four-factor model, we conducted separate regression analyses for the 109 active funds in our sample. For each fund, we regressed its excess returns on the four factors: the excess market return (MKT), the size factor (SMB), the value factor (HML), and the momentum factor (UMD).

Findings from the worst performing funds

This section presents the results as reported in Table 2, beginning the discussion on the performance of the five worst performing funds, with the DIX Norway fund being identified as the poorest performer among them. During its lifespan of nearly 8 years, this fund has consistently exhibited a poor track record. The statistical analysis reveals a statistically significant alpha of -0.001 on a monthly basis, indicating a consistent value destruction for shareholders. Furthermore, the fund demonstrates noteworthy positive exposure to the SMB factor, and negative exposure to the HML factor, suggesting a preference to overweight small-cap stocks and low book-to-market stocks, i.e., a strategy of buying small-cap growth stocks.

Another fund with poor performance, Nordea SMB, had a lifespan of approximately 18 years before it was unsurprisingly closed down 8 years ago. This particular fund had one of the most negative alphas of all the funds in the sample, with an alpha of -0.009. The analysis reveals significant exposure to small-cap stocks, as evidenced by a beta coefficient of 0.379 with strong statistical significance in relation to the SMB factor. The positive beta coefficient for the HML factor further suggest a preference of overweighting high book-to-market stocks. The adjusted R^2 of 0.87 suggests that there might be other factors not included in our model that could explain the value destruction observed in this fund.

APS Oil Energy, on the other hand, had a relatively short existence of merely 5 years before its closure. The statistical analysis shows a strong and statistically significant monthly alpha of -0.012, clearly indicating consistent value destruction throughout its lifespan. Although the adjusted R^2 value of 0.71 implies the presence of other factors not accounted for in the model, the analysis suggests that the fund pursued an unsuccessful counter-cyclical investment approach. Notably, the only statistically significant factor exposure was the UMD factor, with a coefficient of -0.027.

Nordea Vekst had been operational since the beginning of the sample period but was closed the same month as Nordea SMB. The fund exhibited a negative alpha over its lifespan and demonstrated an overweight of small-cap stocks, a strategy that is now becoming a recurring theme for the worst performers.

Lastly, the DNB Norge fund commenced its operation 2 and a half years after the start of the sample period and has remained active since then. The fund also appeared to employ a counter-cyclical approach, with the UMD factor being the only statistically significant factor, in addition to the market factor, identified with a coefficient of -0.012.

Findings from the best performing funds

This section continues our discussion of the results reported in Table 2, now with a focus on the five best performing funds, beginning with the top performer SpareBank 1 Norge Verdi. This fund has consistently delivered abnormal performance over its four-year existence. It exhibits a highly significant monthly alpha of 0.008, indicating a consistent ability to outperform the market. Notably, the fund follows a value-oriented strategy, as evidenced by its positive coefficient in relation to the HML factor. This suggests that the fund focuses on investing in undervalued stocks with high book-to-market ratios.

Danske Invest Norske Aksjer, on the other hand boasts an impressive tenure of 23 years and exhibits a statistically significant monthly alpha of 0.003. Notably, the fund displays unique characteristics with a significant exposure to the UMD factor (-0.021), indicating that they have a counter-cyclical tilt and invests in companies which recently has made downside movements, expecting the trend to shift in their favor after the buy. In addition, the fund has an overweight allocation in high book-to-market stocks in line with a value-oriented investment strategy.

Operating for a little over three years, Fondsfinans Utbytte has demonstrated strong abnormal performance, as indicated by a monthly alpha of 0.007. While none of its coefficients, except for the market factor, are statistically significant, inferring an conclusions about this fund‘s specific investment strategy becomes challenging.

Storebrand Verdi has a tenure of 25 years and continues to exhibit abnormal performance, as evidenced by its alpha of 0.002. Notably, all factors in our model specification are statistically significant for this fund. It displays negative exposure to the SMB factor, positive exposure to the HML factor, and positive exposure to the UMD factor. These results suggests that the fund employs a strategy focused on investing in large-cap companies with high book-to-market ratios that recently performed well.

In its seventh year of operation, Pareto Aksje Norge, consistently outperforms the market, as indicated by its statistically significant monthly alpha of 0.004. The fund follows a strategy of overweighting value stocks, as evidenced by its significant exposure to the HML factor. This suggest a focus on investing in undervalued stocks with high book-to-market ratios, aligning with a value-oriented investment strategy also for this fund.

Table 2: Best/worst active funds

The table displays the regression results for the top 5 best and worst performing funds using the Carhart four-factor model. The point estimates for the alpha and factor loadings are reported along with the adjusted R^2 to explain the percentage of variation the factors has on that specific fund‘s return. The estimates are accompanied by their t-statistics, displayed in parentheses below the respective values. The sample period is 1993-2023.

Individual performance								
Top 5 Best to Worst	Fund	months of obs.	α	β_m	β_{smb}	β_{hml}	β_{umd}	R^2 adj.
1	**SpareBank 1 Norge Verdi**	47	0.008	1.02	-0.036	0.049	-0.034	0.97
			(3.25)	(35.7)	(-0.97)	(1.79)	(-0.97)	
2	**Danske Invest Norske Aksjer**	272	0.003	0.948	-0.017	0.028	-0.021	0.98
			(3.00)	(97.6)	(1.02)	(2.08)	(1.59)	
3	**Fondsfinans Utbytte**	39	0.007	0.925	-0.046	-0.001	0.033	0.95
			(2.24)	(25.6)	(-0.97)	(-0.035)	(-0.741)	
4	**Storebrand Verdi**	300	0.002	0.935	-0.044	0.074	0.036	0.95
			(2.07)	(73)	(-2.29)	(4.35)	(2.26)	
5	**Pareto Aksje Norge**	89	0.004	1.02	-0.038	0.091	-0.023	0.94
			(2.03)	(34.6)	(-1.04)	(3.36)	(-0.67)	
105	**DNB Norge**	329	-0.001	0.975	0.002	0.002	-0.012	0.98
			(-1.78)	(127)	(0.196)	(0.259)	(-2.09)	
106	**Nordea Vekst**	265	-0.002	0.96	0.069	-0.014	-0.006	0.96
			(-1.81)	(74.8)	(3.28)	(-0.72)	(-0.40)	
107	**APS Oil & Energy**	61	-0.012	0.76	0.083	-0.119	-0.027	0.71
			(-2.18)	(8.68)	(0.78)	(-1.31)	(4.00)	
108	**Nordea SMB**	212	-0.009	0.896	0.379	0.095	0.037	0.87
			(-3.94)	(36.4)	(9.36)	(2.34)	(1.09)	
109	**DIX Norway**	92	-0.001	1	0.005	-0.004	0.002	0.99
			(-4.58)	(482)	(1.75)	(-2.05)	(0.69)	

The findings derived from the analysis yield intriguing insights. The worst performing funds consistently exhibited negative alphas, indicative of their inability to generate excess returns, alongside their penchant for overweighting small-cap stocks and low book-to-market stocks, which aligns with a growth-oriented investment strategy. In contrast, the best performing funds consistently exhibited positive alphas, indicating their capability to outperform the market, and implemented strategies centered on investing in undervalued stocks with high book-to-market ratios, as well as focusing on large-cap companies that have exhibited recent strong performance.

These findings strongly suggest the presence of skilled managers within the best performing funds who consistently surpass market benchmarks after accounting for fees. However, to ascertain whether their outperformance can be attributed to skill rather than chance, further analysis is imperative.

6.2 Distinguishing luck from skill – A bootstrap method

Table 3 presents a summary of the bootstrap analysis outcomes. The table displays the funds in descending order based on their actual alpha values which stems from the results from the Carhart four-factor model. The leftmost column shows the rank, starting with the five best performers, followed by the top performers of each percentile, and finally the five worst funds.

Of particular interest is the rightmost column, which represents the outcome of the bootstrap procedure. This column presents the inverse fraction of times that the simulated alpha, generated from 10,000 iterations of the bootstrap procedure, exceeds the actual alpha. These values represent the p-values associated with the null hypothesis, which states that the alpha is solely a result of sampling variation (luck) rather than skill. A p-value below 5 (0.05 multiplied by 100) indicates the rejection of the null hypothesis, suggesting that the observed alpha is attributable to skill rather than luck.

Notably, we find no evidence of skill among the top performers. Therefore, the observed outperformance in the individual performance analysis can be attributed to luck alone. However, in the left tail of the cross-sectional distribution of alphas (worst-performers), we observe p-values below 5, indicating the rejection of the null hypothesis. This suggests the presence of skill among the worst performers. In this context, skill implies that the statistically significant negative alphas are not merely a result of unfortunate circumstances over time, but rather reflect active actions that erode value. This could stem from factors such as poor stock selection, suboptimal timing of overweighting or underweighting stocks relative to the benchmark, or other detrimental strategies employed.

Table 3: Kosowski bootstrap

The table depict the actual and average simulated alphas of the Carhart four-factor model. The leftmost column lists the funds in a descending order according to the actual alpha, including percentiles. We use and list the fund with highest alpha in each percentile. The rightmost column show the fraction of times the simulated alpha is below the actual (i.e the p-value), therefore a fraction less than 5 is statistically significant and indicative of skill. Further, monthly alphas are listed as is, and the sample period is 1993-2023.

	Alphas		
	Actual	Simulated	%(Sim $\leq$ *Act*)
Best	0.00777	0.00003	99.98
2	0.00748	-0.00004	99.38
3	0.00714	0.00003	99.91
4	0.00425	0.00001	98.01
5	0.00384	0.00001	97.09
90%	0.00373	-0.00004	94.43
80%	0.00218	-0.00004	73.63
70%	0.00137	0.00007	62.73
60%	0.00062	-0.000001	63.26
50%	0.00019	0.000009	60.08
40%	-0.00004	-0.0000009	48.62
30%	-0.00034	0.000001	36.66
20%	-0.0012	-0.000022	23.93
10%	-0.0019	-0.0000003	9.61
5	0.00355	0.000026	**4.02**
4	-0.00359	0.00002	**3.9**
3	-0.0042	-0.00001	15.1
2	-0.00972	0.00006	**1.33**
Worst	-0.01169	-0.000015	**1.19**

7 Conclusion

In this thesis, we have undertaken an examination of active mutual fund performance in the context of the Norwegian market, with the aim of investigating whether actively managed funds consistently outperform passive index funds net of fees. A comprehensive assessment of these funds has been achieved by having constructed a survivorship bias free dataset comprising 109 active funds over the period 1993 to 2023. Throughout our analysis we have shown how, on aggregate, active funds perform relative to passive funds. We delved further into individual fund products and their performance, and finally we built a cross-sectional distribution of alphas, following the methodology outlined by Kosowski (2006) to inspect both tails of the distribution and compelling evidence was found on whether the outperformance of actively managed funds was due to luck or skill.

Our findings reveal that, on aggregate, active fund managers generate a monthly alpha of 30 basis points. However, this observed alpha does not attain statistical significance when employing the Fama-French model. Pointing to the fact that when you look at active managers as a whole, they fail to outperform passive index funds net of fees.

Delving into the examination of individual funds, we observe that only a mere 11% of the active funds demonstrate consistent outperformance. This result serves as a cautionary reminder that the majority of active fund managers struggle to consistently outperform the market on a risk-adjusted basis.

Moreover, our rigorous bootstrap analysis provides compelling evidence supporting the notion that the observed outperformance is primarily attributable to luck rather than skill. This substantiates the importance of acknowledging the role of chance in evaluating fund performance and dispelling any unwarranted assumptions regarding the presence of skill among active fund managers. Furthermore, our investigation of the cross-sectional distribution of alphas brings to light an intriguing observation. Specifically, we identify ten fund products positioned in the left tail, in which their performance can be attributed to skill. This suggests that certain fund managers may possess abilities or strategies that result in value destruction, such as poor stock selection or misguided timing decisions.

Despite the challenges and limitations encountered in our analysis, we maintain a belief in the potential of active management. It is worth noting that our research has deliberately narrowed its focus to exclusively examine Norwegian funds with mandates limited to publicly listed Norwegian equities. Consequently, fund managers in this context are constrained to diversifying within a single market and a sole asset class. Furthermore, the Norwegian market, when viewed from a global perspective, exhibits characteristics of relative smallness and high efficiency.

Drawing from our academic training and other empirical findings, we recognize that for an active strategy to consistently outperform its benchmark, a broader scope of diversification is essential across multiple markets and asset classes. An active manager operating with a global mandate, coupled with the flexibility to invest in diverse asset classes such as bonds and private equity, possesses the potential to consistently outperform the overall market net of fees, comparable to entities like Norges Bank Investment Management (NBIM). Examining this premise in the form of a future thesis would offer a compelling avenue for further research.

Another intriguing prospect lies in constructing factor portfolios aligned with the Fama & French five-factor model, and subsequently reevaluating aggregate and individual performance using this framework. This approach holds promise for enhancing the depth and robustness of our analysis.

Overall, our findings paint a discouraging picture for active management in the Norwegian market. For the average investor seeking to invest their savings, the chances of picking an outperforming active manager ex-ante are exceedingly slim, and there is no reliable method to predict which managers will outperform in the future. Our bootstrap analysis revealed that the managers who did outperform did so by chance, indicating that attempting to select an active manager with consistent outperformance is akin to a game of chance.

Choosing to play this game comes with significant risks. Aside from the low likelihood of finding a consistently outperforming manager, there is also the peril of selecting a manager with poor skills who ends up eroding value rather than generating returns. Our recommendation for investing in mutual funds in Norway is therefore to opt for a passively managed index fund that tracks the market benchmark and features low fees. This approach eliminates the risk of choosing an active manager who fails to deliver on their promises and potentially destroys value. Instead, investing in an index fund ensures that your savings grow in line with the overall market in a cost-effective and reliable manner.

APPENDIX

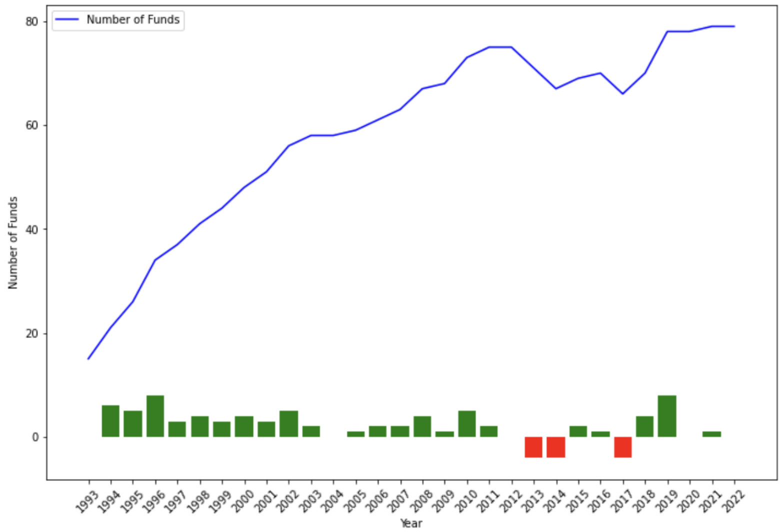

Figure 1 - Appendix The line indicates the number of active mutual funds in operation, and the bars represent yearly increase/decrease of funds over sample period 1993-2023.

Table 1 - Appendix Descriptive statistics - Fund return & Benchmark

This table reports some descriptive statistics for the benchmark and fund returns. The benchmark is of our own creation as described in the text (section 5.4), "Alive" is an equally weighted portfolio consisting strictly of funds available to date, and "All" is an equally weighted portfolio consisting of all 109 funds in our data set. Statistics are calculated from excess returns and reported on a monthly basis, on a number format.

	Mean	**Std**	**Max**	**Min**	**Skew**	**Kurt**
Benchmark	0.0075	0.0749	0.2420	-0.3651	-0.8140	3.4917
Alive	0.0092	0.0737	0.2525	-0.3282	-0.7085	2.827
All	0.0089	0.0731	0.2525	-0.3191	-0.7019	2.7218

Figure 2 - Appendix Forward-looking 1m risk-free rate over sample period 1993-2023

Table 2 - Appendix Descriptive statistics - Factors

This table show summary statistics of the factors over the sample period 1993-2023. Statistics are reported on a monthly basis.

	Rm - Rf	**SMB**	**HML**	**UMD**
average return	**0.0075**	**0.0145**	**0.0007**	**0.0116**
standard deviations	**0.0750**	**0.0491**	**0.0573**	**0.0618**
Max	0.2420	0.2754	0.1804	0.2508
Min	-0.3650	-0.2792	-0.2989	-0.2686
Skew	-0.8106	0.2868	-0.5377	-0.3612
Kurtosis	3.4556	5.3202	2.8003	2.7574

Table 3 - Appendix Cross-correlations - Factors

Cross-correlations of factors over sample period 1993-2023.

cross-correlations	**Rm - Rf**	**SMB**	**HML**	**UMD**
Rm - Rf	1			
SMB	0.0289	1		
HML	0.0627	-0.0435	1	
UMD	-0.1741	-0.0904	-0.0972	1

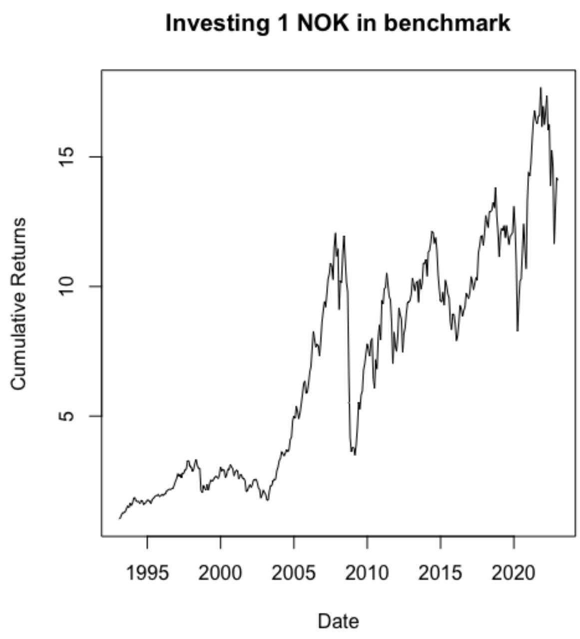

Figure 3 - Appendix Cumulative return of 1 NOK investment in benchmark over sample period 1993-2023

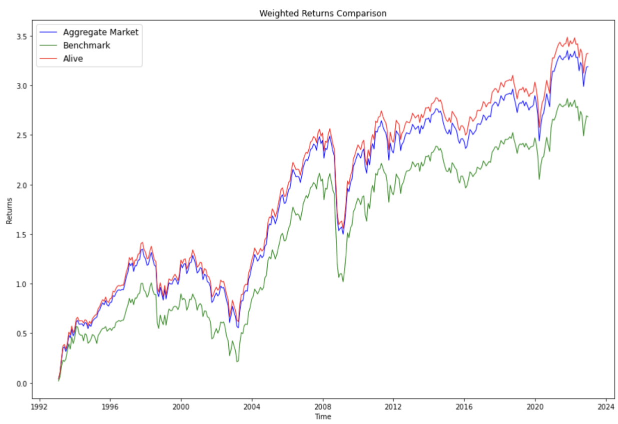

Figure 4 - Appendix Cumulative return of different equally weighted portfolios and benchmark over sample period 1993-2023

REFERENCES

Carhart, M.M. (1997). On Persistence in Mutual Fund Performance. Journal of Finance, 52(1), 57-82. https://doi.org/10.1111/j.1540-6261.1997.tb03808.x

Chen, J. (2020, December 29). Passive Investing. Investopedia. Retrieved from https://www.investopedia.com/terms/p/passiveinvesting.asp

Chen, J. (2023, May 25). Alpha: What It Means in Investing, With Examples. Investopedia. Retrieved from https://www.investopedia.com/terms/a/alpha.asp

Elton, E. J., Gruber, M. J., & Blake, C. R. (1996). The persistence of risk-adjusted mutual fund performance. The Journal of Business, 69(2), 133-157. Retrieved from https://www.jstor.org/stable/2353461

Fama, E.F. (1970). Efficient Capital Markets: A Review of Theory and Empirical Work. The Journal of Finance, 25(2), 383-417. https://doi.org/10.2307/2325486

Fama, E.F., & French, K.R. (1992). The Cross-Section of Expected Stock Returns. The Journal of Finance, 47(2), 427-465. https://doi.org/10.1111/j.1540-6261.1992.tb04398.x

Fama, E.F., & French, K.R. (2015). A five-factor asset pricing model. Journal of Financial Economics, 116(1), 1-22. https://doi.org/10.1016/j.jfineco.2014.10.010

French, K.R. (2008). Presidential Address: The Cost of Active Investing. Journal of Finance, 63(4), 1537-1573. https://doi.org/10.1111/j.1540-6261.2008.01368.x

French, K.R. (2023). Data Library. Retrieved from http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html

Gallefoss, K., Hansen, H.H., Haukaas, E.S., & Molnár, P. (2015). What daily data can tell us about mutual funds: Evidence from Norway. Journal of Banking & Finance, 55, 117–129. https://doi.org/10.1016/j.jbankfin.2015.02.001

Gjerde, Ø., & Sættem, F. (1991). Performance evaluation of Norwegian mutual funds. Scandinavian Journal of Management, 7(4), 297-307. https://doi.org/10.1016/0956-5221(91)90005-L

Grinblatt, M., & Titman, S. (1989). Mutual fund performance: An analysis of quarterly portfolio holdings. Journal of Business, 62(3), 393-416. Retrieved from https://www.jstor.org/stable/2353353

Grinblatt, M., & Titman, S. (1992). The persistence of mutual fund performance. The Journal of Finance, 47(5), 1977-1984. https://doi.org/10.1111/j.1540-6261.1992.tb04692.x

Gruber, M. J. (1996). Another Puzzle: The Growth in Actively Managed Mutual Funds. The Journal of Finance, 51(3), 783-810. https://doi.org/10.1111/j.1540-6261.1996.tb02707.x

Ippolito, R. (1989). Efficiency With Costly Information: A Study of Mutual Fund Performance, 1965-1984. The Quarterly Journal of Economics, 104(1), 1-23. https://doi.org/10.2307/2937832

Jegadeesh, N., & Titman, S. (1993). Returns of Buying Winners and Selling Losers: Implications for Stock Market Efficiency. The Journal of Finance, 48(1), 65-91. https://doi.org/10.1111/j.1540-6261.1993.tb04702.x

Jensen, M. C. (1968). The performance of mutual funds in the period 1945-1964. Journal of Finance, 23(2), 389-416. https://doi.org/10.2307/2325404

Kosowski, R., Timmermann, A., Wermers, R., & White, H. (2006). Can Mutual Fund "Stars" Really Pick Stocks? New Evidence from a Bootstrap Analysis. The Journal of Finance, 61(6), 2551–2595. https://doi.org/10.1111/j.1540-6261.2006.01015.x

Kraus, A., & Litzenberger, R.H. (1976). Skewness Preference and the Valuation of Risk Assets. The Journal of Finance, 31(4), 1085-1100. https://doi.org/10.2307/2326275

Lehmann, B. N., & Modest, D. M. (1987). Mutual fund performance evaluation: A comparison of benchmarks and benchmark comparisons. Journal of Finance, 42(2), 233-265. https://doi.org/10.2307/2328251

Lintner, J. (1965). Security Prices, Risk, and Maximal Gains from Diversification. The Journal of Finance, 20(4), 587–615. https://doi.org/10.1111/j.1540-6261.1965.tb02930.x

Malkiel, B.G. (1995). Returns from Investing in Equity Mutual Funds 1971 to 1991. The Journal of Finance, 50(2), 549-572. https://doi.org/10.1111/j.1540-6261.1995.tb04795.x

Malkiel, B.G. (2003). The efficient market hypothesis and its critics. The Journal of Economic Perspectives, 17(1), 59-82. DOI: 10.1257/089533003321164958

Maples. (n.d). UCITS. Retrived from https://maples.com/en/services/legal-services/funds-and-investment-management/eu-regulated-funds/ucits

Markowitz, H. (1952). Portfolio selection. The Journal of Finance, 7(1), 77-91. https://doi.org/10.2307/2975974

Morningstar (2023). Total Return. Retrieved from https://awgmain.morningstar.com /webhelp/glossary$_{d}efinitions/mutual_{f}und/mfglossary_{T}otal_{R}eturn.html$

Moskowitz, T. J. (2002). Discussion. The Journal of Finance, 55(4), 1695-1703. https://doi.org/10.1111/0022-1082.00264

MSCI. (n.d.). Equity Factor Models Retrieved from https://www.msci.com/our-solutions/factor-investing/factor-models

Sharpe, W.F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. The Journal of Finance, 19(3), 425–442. https://doi.org/10.1111/j.1540-6261.1964.tb02865.x

Sharpe, W.F. (1966). Mutual fund performance. The Journal of Business, 39(1), 119-138. Retrieved from https://www.jstor.org/stable/2351741

Sharpe, W.F. (1991). The arithmetic of active management. Financial Analyst Journal, 47(1), 7-9. https://doi.org/10.2469/faj.v47.n1.7

Storebrand (2023). Skatteregler for fond i 2023. Retrieved from https://www.storebrand.no/privat/sparing/fondssparing/skatteregler-for-fond

Sørensen, L.Q. (2009). Mutual Fund Performance at the Oslo Stock Exchange. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.1488745

Treynor, J.L. (1965). How to rate management of investment funds. Harvard Business Review, 43, 63-75. https://doi.org/10.1002/9781119196679.ch10

Wermers, R. (2000). Mutual fund performance: An empirical decomposition into stock-picking talent, style, transactions costs, and expenses. The Journal of Finance, 55(4), 1655-1695. Retrieved from https://www.jstor.org/stable/222375

Ødegaard, B. A. (2023). My Finance Resources. Retrieved from https://baodegaard.no/